Integrated modelling of the determinants of household food insecurity during the 2020–2021 COVID-19 lockdown in Uganda

Henry Musoke Semakula[1,2,3]* , Song Liang[3], Sarah Lindley McKune[2,4], Paul Isolo Mukwaya[1], Frank Mugagga[1], Denis Nseka[1], Hannington Wasswa[1], Patrick Kayima[1], Simon Peter Achuu[5], Patrick Mwendwa[6] and Jovia Nakato[1]

Abstract

Background The determinants of household food insecurity (HFI) do not act in isolation, and are known to be complex, stochastic, nonlinear, and multidimensional. Despite this being especially true in periods of shocks, studies that focus on integrated modelling of the HFI determinants during the COVID-19 lockdown are scarce, with no available evidence on Uganda. The main objective of this study was to develop Bayesian belief network (BBN) models to analyse, rank, and illustrate the conceptual reasoning, and complex causal relationships among the determinants of HFI during the COVID-19 lockdown. This study was based on seven rounds of Uganda's High-Frequency Phone Surveys data sets collected during the lockdown. A total of 15,032 households, 17 independent determinants of HFI, and 8 food security indicators were used in this study. Metrics of sensitivity, and prediction performance were used to evaluate models' accuracy.

Results Eight BBN models were developed for each food insecurity indicator. The accuracy rates of the models ranged between 70.5% and 93.5%, with an average accuracy rate of 78.5%, indicating excellent predictive performance in identifying the determinants of HFI correctly. Our results revealed that approximately 42.2% of the sampled households ($n = 15{,}032$) in Uganda were worried about not having enough food. An estimated 25.2% of the respondents reported skipping a meal, while 32.1% reported consuming less food. Less than 20% of the households experienced food shortage, hunger, or having nothing to eat. Overall, 30.6% of the households were food insecure during the lockdown. The top five ranked determinants of HFI were identified as follows: (1) households' inability to produce enough food; (2) households' inability to buy food; (3) reduced household income; (4) limited cash assistance, and (5) households' inability to stock adequate food supplies.

Conclusions Ranking, rather than the statistical significance of the determinants of HFI, is crucial as an approach to applied research, as it helps stakeholders determine how to allocate resources for targeted interventions within the constraints of limited funding. These findings emphasize the importance of intervening on the most highly ranked determinants of HFI to enhance the resilience of local food systems, and households' capacity to cope with recurring and unforeseen shocks.

Keywords COVID-19, Bayesian belief networks, Food insecurity, Lockdown, Uganda

*Correspondence:
Henry Musoke Semakula
henry.semakula@mak.ac.ug; semhm2000@yahoo.co.uk
Full list of author information is available at the end of the article

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Introduction

The Coronavirus disease (COVID-19) caused by the severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2) was declared a global pandemic on 11th March 2020 by the World Health Organization (WHO). This pandemic had far-reaching consequences globally, impacting various aspects of daily life, including health, education, the economy, and food security among others [1]. Over 240 million people were infected with COVID-19 worldwide, of whom nearly 5 million died [2]. In keeping with WHO guidelines [3], governments implemented a range of restrictions, and measures (i.e., travel restrictions, border closures, quarantine, closure of non-essential services, social distancing, curfews and total lockdown) in an attempt to contain the spread of the disease [4]. However, the enforcement of these stringent measures inevitably disrupted peoples' way of life, significantly affecting all the four pillars of food security, namely, food availability, food accessibility, food utilization, and stability [5]. Studies have shown that the COVID-19 containment measures led to reduced labour mobility, loss of employment, income and associated purchasing power, increase in poverty and food prices, food export restrictions, disruption in food production and food supply chains, thereby creating food insecurity among households [6–9].

Background

The pandemic presented an additional significant threat to food security and nutrition particularly in developing countries, exacerbating existing challenges posed by climate change, economic shocks, desert locusts, conflicts, and insecurity [10]. The effects of the pandemic created major setbacks in registering any significant stride in realising Sustainable Development Goal (SDG) 2 which targets ending hunger, and ensuring access to adequate food for all (SDG Target 2.1), as well as eliminating all forms of malnutrition (SDG Target 2.2) [11].

Globally, it is estimated that between 702 and 828 million people were affected by hunger in 2021, with an increase of approximately 150 million since the onset of the pandemic [11]. While the impact on nutrition security has not been adequately captured, it is feared that the pandemic might have contributed to the consumption of poor-quality diets which are associated with different forms of malnutrition, including under nutrition, micronutrient deficiencies, overweight, and obesity [11].

In Africa, approximately 278 million people faced hunger during the pandemic [11], and the disadvantaged groups, such as women, children, youth, low-skilled workers, and those in the informal sectors, were disproportionately negatively affected [1]. There were also differential impacts experienced at country level. For example, in Kenya and Uganda, it is estimated that the proportion of food insecure households increased by 38% and 44%, respectively, while the regular consumption of fruits decreased by about 30% in both countries [8].

Although COVID-19 exacerbated household food insecurity (HFI) in many developing countries already struggling with widespread poverty, hunger, and malnutrition [6, 7], it should be noted that the determinants of food insecurity at household level are complex, and multidimensional, and differ from one household to another [12]. Given this complexity, and the multidimensionality of HFI, robust models predicting factors that influenced HFI during the pandemic are urgently required to facilitate rational decisions in improving the resilience of households to future shocks—or their ability to absorb, and recover from those shocks without major consequences. Most food insecurity studies during the pandemic used the food insecurity experience scale (FIES), which was developed by the Food and Agriculture Organization [13]. The FIES is a globally accepted set of indicators for measuring progress towards the achievement of SDG 2, and consists of eight short questions related to four broad areas: (1) uncertainty about food supply, (2) compromise on food variety and quality, (3) insufficient food intake, and (4) experiencing hunger [13].

Although different studies have employed different models to analyse the determinants of HFI during the pandemic, this study examined those used to understand the situation in sub-Saharan Africa (SSA). The first comprehensive studies to track HFI, and its determinants during the pandemic basing one multi-country and multi-wave evidence from SSA, used the probit regression and fixed-effects linear probability models and these approaches revealed that female-led households, low education levels of the household head, income loss, increases in prices of major food items, and inadequate safety nets, were the key determinants of HFI [14, 15]. A study conducted in Ethiopia used a random effect model, and revealed that limited access to financial services, loss of farm income, unemployment, loss of income from properties and investments, and lack of assistance from non-governmental organizations (NGOS), were associated with HFI [16]. A study conducted in Kenya, and Uganda used a probit regression model, and concluded that HFI during the pandemic was attributed to the loss and reduction in income, reduced access to markets, and low purchasing power [8]. Another study conducted in Uganda utilizing the High-Frequency Phone Surveys (HFPS) data used both the probit regression model and ordinary least squares estimation method, and this study found out that job loss, large household size, and income loss were the key determinants of HFI [17]. Other studies have employed logistic regression models to analyse the

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determinants of HFI, diet quality,and nutrition during the pandemic [9].

While these, and other previous studies have investigated the determinants of HFI during the pandemic, and offer useful insights, they still have potential limitations, based on the traditional statistical models used, and their limited coverage. First, the traditional models employed in these studies were used to measure the statistical significance of each independent determinant of HFI, without any form of importance ranking to inform policy. Second, the models that represent linear relationships using logistic regressions, struggle with restrictive expressiveness and predictive performance, and sometimes multiplicative interpretation of their results is difficult [18]. Third, the models were unable to represent conceptual reasoning [19] or interactions [18] among determinants of HFI, an important consideration given the cascading effects of the lockdown. Conceptual reasoning can effectively organize and represent knowledge which can efficiently be utilized in advanced applications [19] to inform policy. Fourth, the models were not capable of handling causal relationships [20] among determinants which, were complex, stochastic, nonlinear, multidimensional, and which did not act in isolation [8, 9]. Besides the model limitations of previous studies, the severity of HFI as per the food insecurity indicators was not adequately captured.

To address the limitations of existing research, this study utilized a Bayesian belief network (BBN) modelling approach, an alternative to traditional research models, to analyse, estimate, and rank the determinants of HFI in Uganda during the pandemic. BBNs are robust probabilistic methods that excel in modelling uncertainties, and complex environmental domains, offering advantages over traditional statistical models [21–23]. They are transparent, flexible in modelling causal relationships, capable of integrating information from various sources, can handle uncertainties, and missing data effectively. Moreover, BBNs facilitate visual communication of model results, and allow for continuous updates as new knowledge becomes available [24].

Because of their versatility, BBNs have successfully been used in several modelling exercises including but not limited to, environmental and ecological modelling [22], modelling of chemical food safety hazards [25], food quality, and safety scandals [26], and predicting food fraud products [27]. Despite their popularity, BBN models have not been used in food security studies before, and during the COVID-19 lockdown in Uganda and elsewhere. Thus, we developed BBN models for the eight FIES indicators of food insecurity based on evidence from seven rounds of Uganda's HFPS data sets. Specifically, this study aimed to: (1) develop novel, and effective knowledge-based BBN models illustrating the conceptual reasoning and complex causal relationships among the determinants of HFI during the lockdown; (2) determine the severity of HFI during the pandemic in relation to the food insecurity indicators; (3) rank, and estimate the contribution of the key determinants to HFI observed during the lockdown.

The contributions of this study to the growing body of literature on food security under the COVID-19 pandemic are four-fold. First, a novel BBN modelling approach was utilized to exploit nationally representative and repeated phone survey data covering the lockdown period between March 2020 and December 2021 in Uganda. Second, this study provides new evidence on the prevalence, and key determinants of HFI in Uganda during the pandemic. Third, unlike the previous studies, the graphical representations of the developed BBN models make it easy to visualize the determinants of HFI as well as communicate the results. Fourth, this study is also the first to use BBN models to rank, and estimate the contributions of each independent determinant to HFI. Ranking and prioritizing determinants of HFI are crucial for allocating resources to targeted interventions when operating within a context of limited resources. Using Uganda's HFPS data sets, and a BBN modelling approach, this study provide new insights that will help to expand an understanding of how households fared throughout the pandemic lockdown.

Materials and methods
Study area and justification
This study focused on Uganda (Fig. 1), where agriculture contributes 24.8% of the country's Gross Domestic Product, and engaging over 70% of the country's population [28]. Uganda provides an interesting case to analyze the impact of the COVID-19 lockdown on household food security, because it had a rising level of vulnerability among its population preceding the COVID-19 pandemic [17]. First, Uganda remains one of the most food insecure and poorest country in the world, with more than 70% of its people living below the international poverty line [29]. Second, with a population of over 47.2 million people, Uganda has one of the fastest annual population growth rate of 3.1% [30]. Third, youth unemployment, and national unemployment stand at 13.3% and 8.8%, respectively [31]. Fourth, few Ugandan households own land, and the available agricultural land is infertile, and excessively fragmented into small plots which cannot support meaningful and productive agriculture [28]. Considering that Uganda like many other countries undertook several stringent COVID-19 containment actions starting on the 18th of March 2020, including travel restrictions, cancellation of public gatherings, social distancing, curfew, and
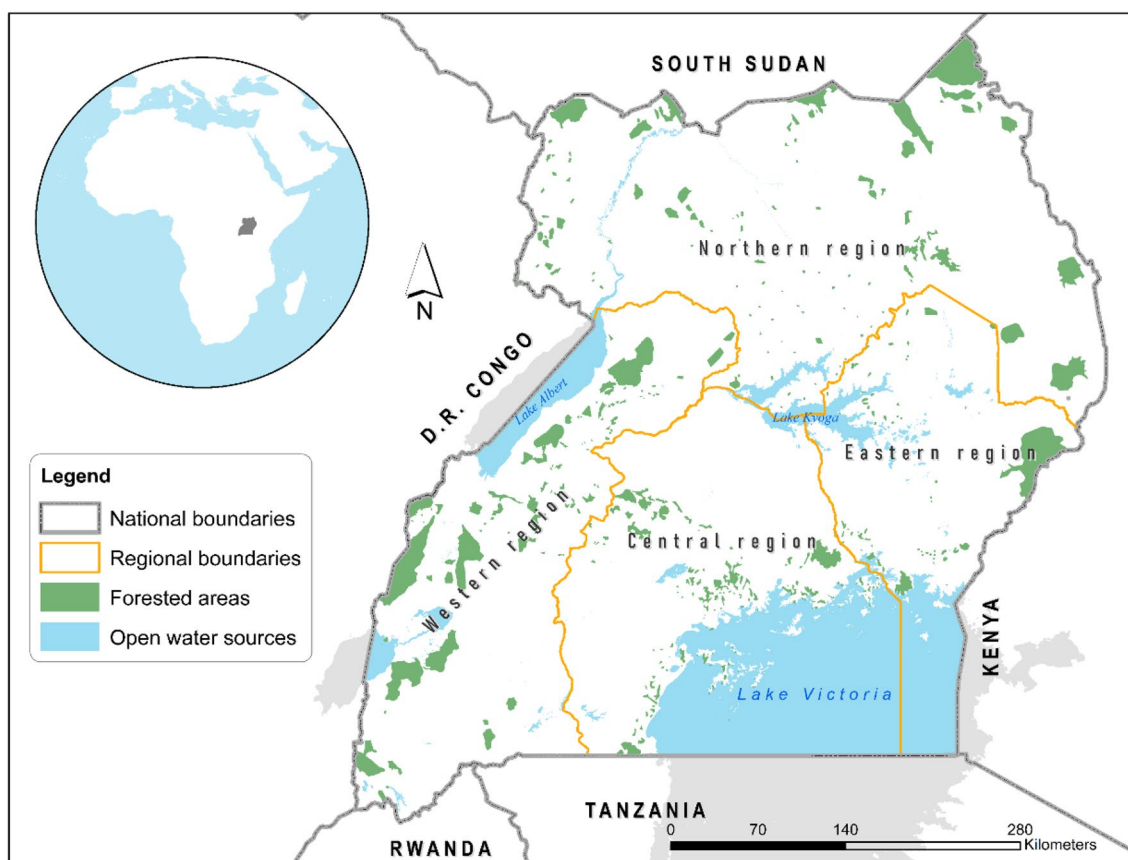
Fig. 1 Map of Uganda

imposed one of the longest ever recorded national and global lockdown [8, 17], this presented a unique study area to examine how households maneuvered with securing food throughout the tough pandemic period.

Bayesian belief network (BBN)

A BBN is a directed acyclic graph (DAG) containing the 'parent' and 'child' nodes connected by edges with a direction associated with them with no feedback loops [22]. The DAG structure can accommodate conceptual reason about an uncertain domain. The nodes of a BBN represent a set of random variables, i.e., $\mathbf{M} = M_1.....M_i,....M_n$, which are pairs linked with connecting arrows (i.e., $M_i \rightarrow M_j$) representing the dependence relationship between variables, with each node containing a conditional probability table quantifying the probabilistic causal relationships among the 'parent' and 'child' nodes [32]. All nodes contain mutually exclusive states (i.e., categorical, Boolean, continuous, or discrete) and are linked by probabilities (i.e., priori or unconditional, conditional, and posterior probabilities) to describe a network of complex interactions [22, 33].

Specifically, "parent" nodes always contain prior or unconditional probabilities of their states determined from actual existing conditions, and these are then linked to the "child" or intermediate nodes with conditional probabilities obtained from experimental data, historical data, and expert opinion or in combination. Output nodes consist of posterior probabilities reflecting an update of the entire chain of conditional probabilities of all states connected to nodes given certain evidence. The BBN model considers uncertainty explicitly based on the Bayes uncertainty of conditional probability dependencies between variables [34]. The Bayes' theorem can be computed by the following formula:

$$P(X|Y) = \frac{P(X) * P(Y|X)}{P(Y)}$$

where P(X) is the prior probability of the hypothesis X (i.e., the likelihood that X will be in a particular state, prior to consideration of any evidence); P (Y|X) is the conditional probability (i.e., the likelihood of the evidence, given the hypothesis to be tested); and P (X|Y) is the posterior probability of the hypothesis (i.e., the

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likelihood that X is in a particular state, conditional on the evidence provided). This equation gives an explicit representation of uncertainties [34].

Application of the BBN modelling approach to the food insecurity

The procedure used to develop the BBN models in this study was based on well-established guidelines on BBN modelling protocols [35, 36]. During the initial development of BBN models, prior knowledge on the problem understudy is of considerable significance in determining the structure, and model parameters [35]. In this study, prior knowledge about the determinants of household food insecurity during the lockdown was obtained from literature, expert knowledge, and Uganda's HFPS data sets.

In this study, a comprehensive survey of relevant literature on determinants of household food insecurity during the COVID-19 was conducted. The search for relevant publications utilized selected criteria established by Wondimagegn Mengist, and colleagues [37], and some components of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [38]. First, the searching strings, and terms were determined [i.e., "COVID-19" AND "agriculture", "COVID-19" AND "food security", "COVID-19" AND "farming", "COVID-19" AND "Nutrition", "effects of COVID-19 on food security", "hunger AND lockdown"] to obtain publications relevant to the study. The search was done in four internationally recognised databases most relevant for the study: MEDLINE (Pubmed®), EMBASE®, Scopus®, and Web of Science®. Google scholar, and Mendeley search engines were also used to obtain more relevant literature not covered in the databases. Second, the publications extracted for review, were only those, which met the following criteria. Publications:

i)   published in scientific peer-reviewed journals
ii) related to food and agriculture
iii) written in the English language
iv) published after 2020
v)   with predefined keywords existing as a whole or at least in the titles, keywords or abstract section of this papers.
vi) with relevancy to the Africa and Uganda
vii) accessible
viii) not duplicated within the searched publications.

After the rigorous screening, 20 publications met the above criteria, downloaded, and later reviewed. Literature review is an integral step in the development of a BBN model, providing a foundation of knowledge, validating model choices, contributing to the robustness and effectiveness of the model as well as enhancing the overall reliability and validity of the model [35, 36]. It ensures that the model is well-informed, reflects the current state of knowledge in the field, and contributes meaningfully to the understanding of complex systems [21, 22]. In this study, literature review was conducted to: (1) gain a deep understanding of the food security situations during the pandemic in Sub Saharan Africa (SSA); (2) identify, and select the most relevant variables for inclusion in the BBN models as captured in HFPS data sets, and (3) gain comprehensive knowledge on the relationships among these variables, and how they influenced an outcome of interest (i.e., food insecurity). Based on the literature review, expert knowledge, and the HFPS data sets, 17 independent explanatory variables, and 8 food insecurity indicators were identified as summarized in Table 1.

Based on the previous BBN modelling experience by some of authors of this paper [50–52], knowledge from literature review, together with online consultations, and feedbacks from three experts on BBN development, all the determinants and food insecurity indicators in Table 1 were organized into an influence diagram as shown in Fig. 2.

Data sets for developing the BBN models

The HFPS data sets from Uganda were used in this study. These data sets were used to: (1) ensure that the developed models align with the perceptions, and experiences of respondents who were affected by food insecurity during the pandemic; (2) enhance the accuracy of the developed BBN models, and their relevance while leveraging the collective responses of individuals who were directly affected by food insecurity during the pandemic; (3) compare authors' initial assumptions with the perceptions of survey participants, ensuring that the models accurately represented the beliefs and knowledge of survey respondents; and (4) assess the performance of the developed BBN models.

The HFPS data sets used in this study were a result of an unprecedented data collection efforts by the Uganda Bureau of Statistics and World Bank aimed at producing real-time information on the socio-economic impacts of COVID-19 on households, and individuals in Uganda. The high-frequency surveys were designed to be nationally representative. Since the onset of the COVID-19 pandemic in Uganda, the World Bank has been leveraging the Living Standards Measurement Study—Integrated Survey on Agriculture (LSMS-ISA) program to support high-frequency phone surveys on COVID-19 in Uganda. Ten rounds of surveys have been conducted in Uganda between June 2020 and November 2022, as shown in Table 2.

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Table 1 Key determinants of food insecurity purposively selected for constructing BBN models

Sn	Determinants of food insecurity	References
	Independent variables	
1	Age of the household head	[8, 9, 14, 16, 17, 39, 40]
2	Gender of household head	[12, 14, 17, 39, 40]
3	Ability to work in non-farm business	[14, 17, 39, 40]
4	Household's ability to access assistance	[14, 17, 39, 40]
5	Household size	[14, 17, 39, 40]
6	Revenue status from business	[14, 17, 39–41]
7	Location of household	[17, 40]
8	Wage payment status	[14, 17, 40]
9	Total household income	[7, 41–45]
10	Total value of assistance obtained	[9]
11	Ability to work in wage employment	[40]
12	Ability to work in agriculture production	[7, 9, 14, 40, 41, 46–48]
13	Household's ability to obtained money from agriculture produce	[7, 9, 14, 40, 41, 46–48]
14	Ability to produce enough food	[14, 40, 41]
15	Ability to stock enough food	[8, 9, 16, 40, 49]
16	Ability to access food markets	[9, 10, 40]
17	Ability to buy food	[7, 9, 14, 40, 41, 46–48]
18	Dependent variables (Food security indicators (i.e. 1) not having enough food to eat; (2) unable to eat healthy food; (3) ate few kinds of food; (4) skipped a meal; (5) ate less food; (6) ran out of food; (7) went hungry, and (8) went without food for a whole day)	[13]
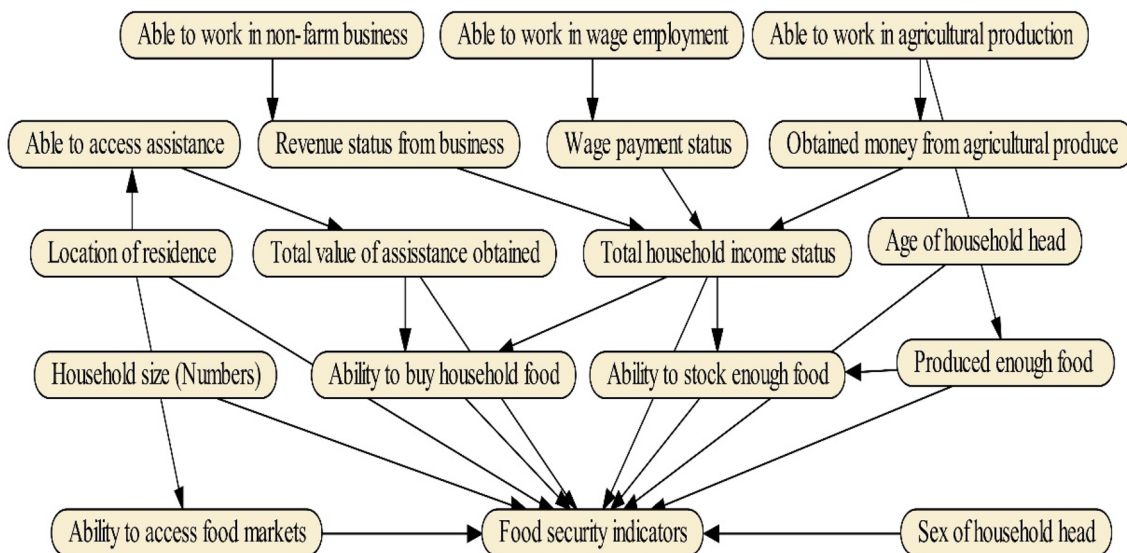
Fig. 2 Influence diagram depicting the causal-effect relationships among key explanatory determinants that influence household food insecurity

However, this study focused on data sets from seven rounds, which were collected during the strict enforcement of COVID-19 containment measures, and total lockdown (i.e., between March 2020 and December 2021). This period was selected to understand how households in the country responded to the evolving food insecurity crisis during that time.

From the seven rounds of survey collection, a total of 15,032 households were included in this study; the 17 independent determinants, and 8 food security indicators

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Table 2 Ten rounds of high frequency phone surveys data collected in Uganda

Cycles	Start date	End date	Number respondents
Round 1	03/06/2020	16/06/2020	2227
Round 2	30/07/2020	19/08/2020	2199
Round 3	14/09/2020	16/10/2020	2179
Round 4	27/10/2020	17/11/2020	2136
Round 5	02/02/2021	18/02/2021	2122
Round 6	22/03/2021	09/04/2021	2100
Round 7	20/09/2021	15/11/2021	1950
Round 8	21/06/2022	15/07/2022	1881
Round 9	05/08/2022	29/08/2022	1871
Round 10	12/10/2022	05/11/2022	1668

extracted from these data sets, are shown in Table 1, and Fig. 2. It should also be noted that in January 2022, Uganda lifted its 2-year world's longest lockdown. As previously indicated, data from rounds 8 to 10, collected afterwards, were not used in this study. Data compilation was conducted using JMP software, version 13 (JMP Statistical Discovery LLC, North Carolina, USA).

Model development and parameterization
Using Netica software version 6.09 (Norsys Software Corp. Vancouver, Canada), the influence diagram (Fig. 2) was turned into 8 BBN models corresponding to the 8 food security indicators. The HFPS data sets were used to parameterize the BBN models. The structured BBN models consisted of nodes representing independent explanatory determinants, linkages with nodes showing direction of probabilistic causation, and the response outcomes (i.e., food insecurity indicators). In the structured BBN models, "parent" nodes fed into "child" nodes and following through the networks, some "child" nodes became "parents" of others. States in the BBN models were created according to the determined categories, and codes as captured in the standardized questionnaires, which were used in the high-frequency phone surveys. The states were limited to between 2 and 4 per node to reduce the complexity of conditional probability tables (CPTs) while obtaining the desired precision, and prediction of estimates that captured the corresponding range of input values from the data sets. In the constructed BBN models, the nodes representing variables, and states were linked by CPTs containing corresponding probabilities.

Calibration of the BBN models
The compiled data file ($n = 15,032$ households) generated from the seven rounds of HFPS was converted into a Microsoft Excel casefile compatible with the Netica software. Using the K-fold partitioning approach ($K = 2$), the compiled casefile ($n = 15,032$) was randomly partitioned into eight training portions (70%, $n = 10,523$) which were used to populate the eight models, and eight test data sets (30%, $n = 4509$) that were used to evaluate the accuracy of the models. A 70/30 data split is among the standard partition ranges recommended for model calibration, and testing [53]. Both the training and testing data sets were generated using JMP 13 software. The vertical lookup (V-lookup) function in Microsoft Excel was used to extract the randomly partitioned portions (i.e., training and testing data sets) from the main casefile ($n = 15,032$). The training data sets were entered into the BBN models as findings. Learning of the CPTs was based on expectation maximization learning algorithm, a robust technique which automatically updates initial parameter estimates by fitting the data file to the final model [23].

Validation and assessment of models
The accuracy of the developed BBN models was evaluated using metrics of sensitivity and prediction performance [33]. In the sensitivity analysis, variables that had the most influence on the food insecurity indicators and the causal relationships of importance were identified using the mutual information (entropy reduction) values. Mutual information represents the symmetric between two nodes, and is a measure of magnitude with which a finding at one node (i.e., explanatory/ independent node) is expected to alter the beliefs (measured as entropy reduction) at another node (the query/dependent node) [33]. The function of 'sensitivity to findings' in Netica software was invoked on the output nodes (i.e., food insecurity indicators) to calculate the entropy reduction for the other variables in the networks, and the results were expressed as a percentage of the total entropy of the query output nodes.

Under the prediction performance, the randomly generated test data set (30%, $n = 4509$), was used to evaluate the accuracy of models using the 'test with cases' function of Netica software. Although various standard test metrics can be used to evaluate the BBN model performance [33], in this study, we used the error rates, and scoring rules of logarithmic loss, quadratic loss, and spherical payoff to determine how well the state belief levels in the developed BBN models overlapped with values in a casefile. For logarithmic loss (0–infinity), and quadratic loss (0–2) ranges, scores close to zero are considered to be better, while 1, indicates the best model performance for spherical payoff (0–1) [33, 54].

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Results

The developed Bayesian belief network models

In this study, eight BBN models were developed, each focusing on the respective food insecurity indicator to illustrate the conceptual reasoning, and interactions among the determinants of HFI during the COVID-19 lockdown in Uganda, as shown in Fig. 3, and Additional file 1: Fig. S1, Additional file 2: Fig. S2, Additional file 3: Fig. S3, Additional file 4: Fig. S4, Additional file 5: Fig. S5, Additional file 6: Fig. S6 and Additional file 7: Fig. S7.

The BBN models (Fig. 3 and Additional file 1: Fig. S1, Additional file 2: Fig. S2, Additional file 3: Fig. S3, Additional file 4: Fig. S4, Additional file 5: Fig. S5, Additional file 6: Fig. S6 and Additional file 7: Fig. S7.) demonstrate a joint probability distribution of determinants that are shown as nodes and linked with arrows. The output nodes (i.e., the respective food insecurity indicators) show a collective effect of all determinants expressed as posterior conditional probabilities. Regarding the performance of the models, the error rates ranged between 6.5% and 29.5% (Fig. 4) with an average error rate of
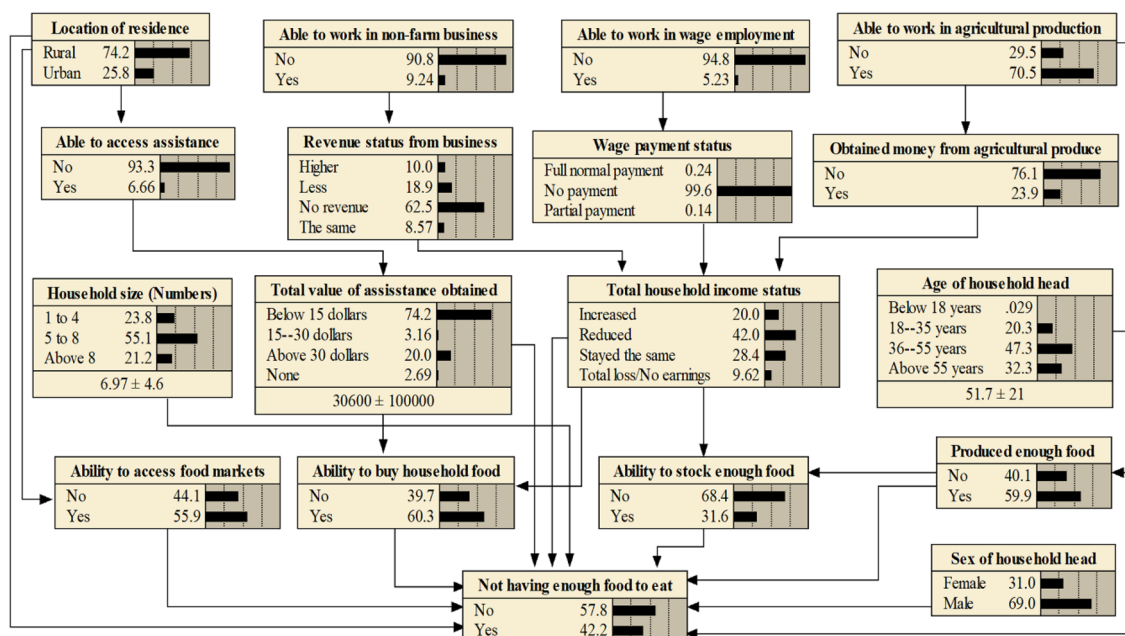

Fig. 3 BBN model depicting the interaction among the determinants of food insecurity indicator 1(i.e., not having enough food to eat)
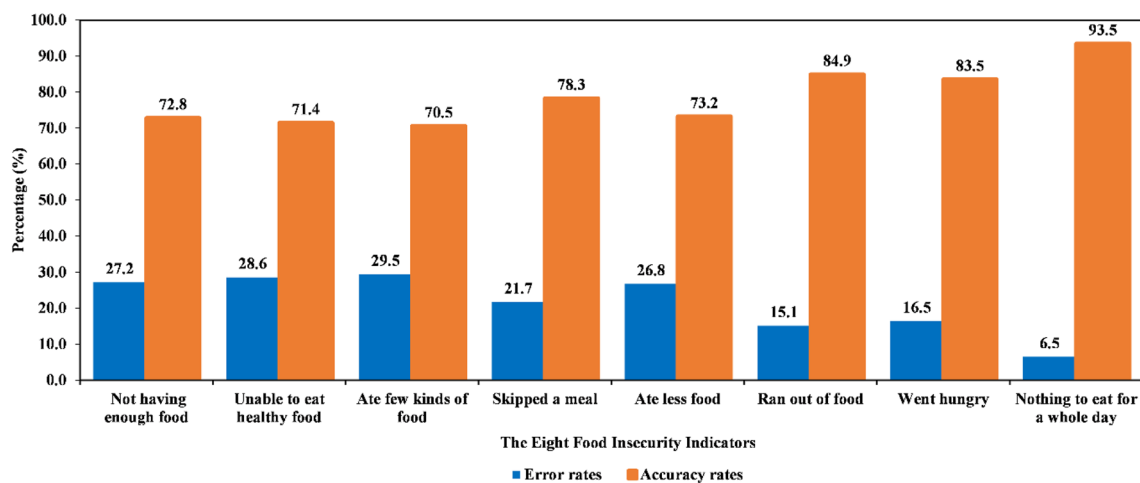

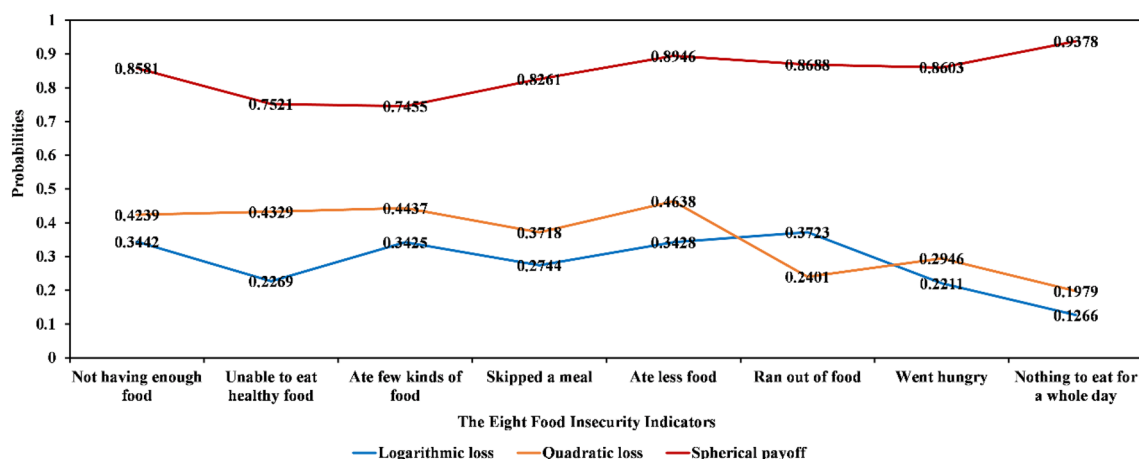**Fig. 4** The error and accuracy rates of the eight HFI BBN models

Fig. 5 The scoring rules of the developed BBN models

21.5%. The accuracy rates for the models ranged between 70.5% and 93.5% (Fig. 4) with an average accuracy rate of 78.5%, implying that all the models were excellent in predicting the determinants of HFI correctly.

The classification power of the developed BBN models was evaluated using the scoring rules. The scoring rule results illustrate a strong predictive power of the BBN models with both the logarithmic loss and quadratic loss scores close to zero (Fig. 5). The spherical payoff scores, which are close to 1, indicate the excellent performance capacity of the models to predict the determinants of HFI during the lockdown (Fig. 5).

Prevalence of household food insecurity during the lockdown in Uganda

In this study, the posterior conditional probabilities from the output nodes of the developed eight BBN models

(Fig. 3 and Additional file 1: Fig. S1, Additional file 2: Fig. S2, Additional file 3: Fig. S3, Additional file 4: Fig. S4, Additional file 5: Fig. S5, Additional file 6: Fig. S6 and Additional file 7: Fig. S7.) were used to illustrate the prevalence of each food insecurity indicator during the COVID-19 lockdown as can be visualised in Fig. 6.

In Fig. 6, the probability of the sampled households in Uganda to be worried of not having enough food during the lockdown was 42.2%. This worry might have been attributed to the pandemic-induced jobs and income losses, which left many households wondering how they would survive during the tough period [40]. About 50% of the respondents were unable to eat healthy foods. This situation was worsened by the low purchasing power, limited mobility, and market access restrictions that retarded households' ability to buy or look for nutritious foods. This study result is in-line with the findings
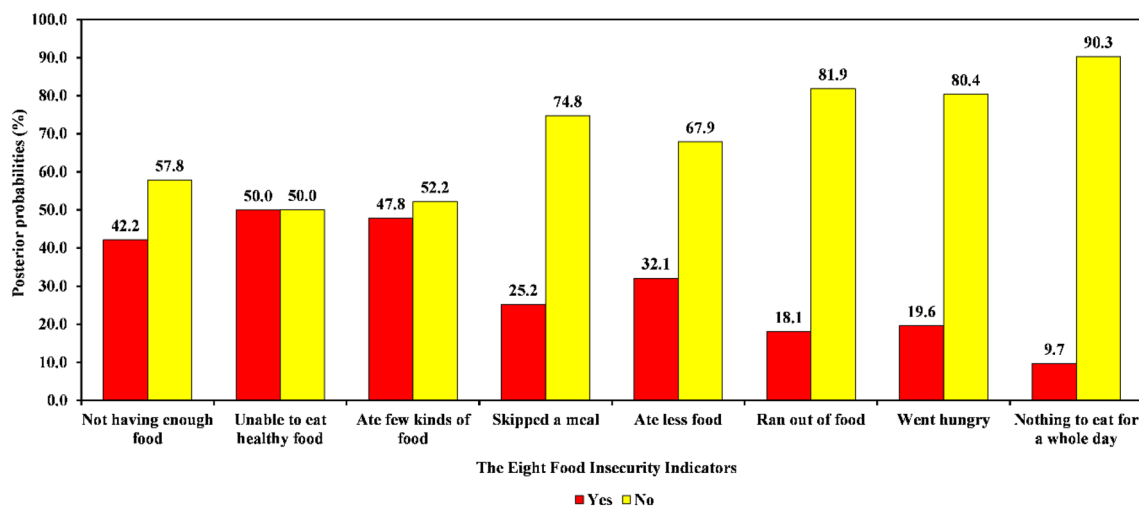

Fig. 6 The prevalence of HFI across the eight indicators during the COVID-19 lockdown in Uganda

of two studies done in Uganda. The first study involving 442 respondents revealed that consumption of healthy foods, namely, fruits, vegetables, fish, meat, and poultry products dropped by 50 percentage points during the pandemic in Uganda [8]. The second study showed that, a reduction in wage income significantly increased incidences of households eating non-healthy by 43.7% [17].

The reduction in income, and increased cases of food insecurity is not surprising, because most households in Uganda are prominent buyers of staple foods, and thus, must rely on markets for foodstuffs that they do not produce. Thus, any form of income reduction would make many households vulnerable, and could increase the prevalence of food insecurity amongst them. From Fig. 6, it can be vividly observed that only 25.2% of the respondents skipped a meal and 32.1% ate less food. Less than 20% of the sampled households ran out of food, went hungry, or had nothing to eat (Fig. 6). Though prevalence of these indicators are among the lowest of the eight food insecurity indicators, these rates are still high compared to other available data for Uganda.

Ranking the determinants of household food insecurity during the lockdown in Uganda

This study considered 17 determinants of HFI as shown in Fig. 3. Sensitivity analysis was performed on the output nodes of the eight BBN models (Fig. 3 and Additional file 1: Fig. S1, Additional file 2: Fig. S2, Additional file 3: Fig. S3, Additional file 4: Fig. S4, Additional file 5: Fig. S5, Additional file 6: Fig. S6 and Additional file 7: Fig. S7.) to rank the importance of each determinant to the respective food insecurity indicators. The ranks were based on the entropy reduction results (Additional file 8: Table S1, Additional file 9: Table S2, Additional file 10: Table S3, Additional file 11: Table S4, Additional file 12: Table S5, Additional file 13: Table S6, Additional file 14: Table S7, Additional file 15: Table S8 and Additional file 16: Table S9) and summarized in Fig. 7.

In Fig. 7, the inability of households to produce enough food was the number one ranked determinant across the seven food insecurity indicators. This might have been attributed to lack of access to farm inputs (i.e., seeds and fertilizers), limited labour mobility, and social distancing. The inability of households to buy food was ranked number two across four food insecurity indicators (i.e., not having enough food, ate few kinds of food, unable to eat healthy food, and skipped a meal) (Fig. 7). This was attributed to market access restrictions, mobility restrictions, high food prices, inadequate incomes, and scarcity of food items [8, 17]. Reduced household income was ranked number three across seven food insecurity indicators (Fig. 7). The stringent implementation of COVID-19 containment measures resulted into job, and income

losses which translated into heightened food insecurity at the household level [8]. Less cash assistance was ranked between 1 and 4 across six food insecurity indicators (Fig. 7). The results further indicate that sex of the household head, age of the household head, location of residence, household size, reduced revenue from business, reduced wage payments, inability to work on wage employment and non-farm business, were not among the top five ranked determinants (Fig. 7).

Predicting the impact of COVID-19 lockdown on food insecurity indicators

After performing the sensitivity analysis (Fig. 7), the top five ranked determinants of HFI were selected as examples to estimate their contribution to the food security indicators by performing a scenario analysis. In the scenario analysis, the output nodes of the BBN models (Fig. 3 and Additional file 1: Fig. S1, Additional file 2: Fig. S2, Additional file 3: Fig. S3, Additional file 4: Fig. S4, Additional file 5: Fig. S5, Additional file 6: Fig. S6 and Additional file 7: Fig. S7.), were focused on, where the 'Yes' state beliefs were tagged to the probability of 1 (i.e., food insecurity occurred) to reveal the estimated changes in the determinants as shown in Table 3. Furthermore, in Table 3, changes in state beliefs were used to calculate percentage point differences for each determinant to express their contribution to the respective food insecurity indicators. A positive percentage point difference meant that households were food insecure, while a negative percentage point difference meant that households were food secure during the lockdown.

In Table 3, the inability of households to produce enough food affected all the eight food insecurity indicators, which increased between 6.96 and 12.56 percentage points. The inability of households to buy food also increased all the food insecurity indicators between 2.94 and 6.76 percentage points. Households that experienced income reductions, or no earnings, saw all their food insecurity indicators affected, and increased between 0.07 and 7.92 percentage points. Thus, interventions are required to help households diversify income sources that can increase food varieties, and reduce their vulnerability to food insecurity during times of hardships. The inability to access markets only increased food insecurity indicators 1, 2, 3, and 5 (between 0.78 and 2.5 percentage points). All the eight food insecurity indicators increased between 0.03 and 7.78 percentage points in all households that received cash assistance below 30 dollars or none (Table 3). Similar observations have been made in studies conducted in SSA, where it revealed that limited cash assistance increased the chances of food insecurity among households during the pandemic [14, 15]. However, there are some determinants that only affected
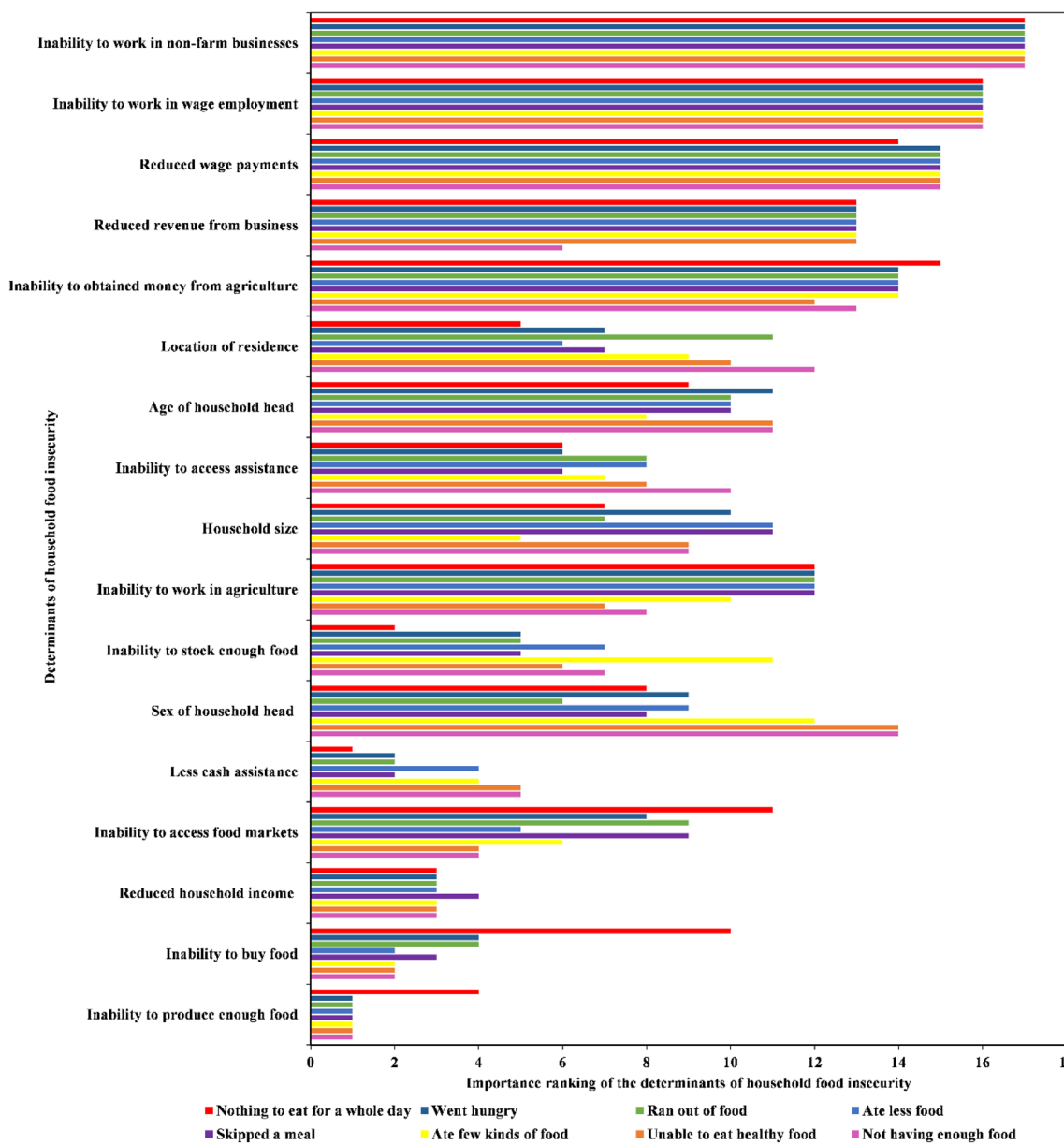
Fig. 7 Ranking of the determinants of household food insecurity during the lockdown in Uganda

one food insecurity indicator. For instance, households with over 8 persons, their only food insecurity indicator affected was *'ate few kinds of food'*, which increased by 0.68 percentage points. This result is consistent with another study conducted in Uganda, where it was revealed that larger households were more likely than smaller households to reduce the consumption of nutritious foods including fish, fruits, vegetable, meat, and poultry during the COVID-19 crisis [8].

Meanwhile, in female-led households, the only affected food insecurity indicator was *'ran out of food'*,

which increased by 4.07 percentage points. This finding is consistent with other studies that have shown that female headed households to be more vulnerable to food insecurity during the pandemic as compared to male headed households [6, 8, 9, 14, 15, 40]. Finally, for urban-based households, the affected food insecurity indicator was *'went without food for a whole day'*, which increased by 7.56 percentage points. This was particularly common in slum areas, where households lost their jobs, and could not buy food. Although some households in slums were given some form of food

Table 3 The contribution of the determinants to each food insecurity indicators

Nodes and states	Initial state-beliefs[a]	New state-beliefs[b]	Changes in beliefs[c]	Percentage point change
Indicator 1: Not having enough food to eat				
No	0.57845	–	–	–
Yes	0.42155	**1 ***	–	–
Produced enough food				
No	0.40118	0.49322	0.09204	9.20[†]
Yes	0.59882	0.50678	− 0.09204	− 9.20
Ability to buy food				
No	0.60279	0.63862	0.03583	3.58[†]
Yes	0.39721	0.36138	− 0.03583	− 3.58
Total household income status				
Increased	0.19967	0.19518	− 0.00449	− 0.45
Reduced	0.41969	0.43030	0.01061	1.06[†]
Stayed the same	0.28443	0.26651	− 0.01792	− 1.79
No earnings	0.09621	0.10801	0.01180	1.18[†]
Ability to access food markets				
No	0.55910	0.58130	0.02220	2.22[†]
Yes	0.44090	0.41870	− 0.02220	− 2.22
Total value of assistance				
Below 15 dollars	0.74184	0.75167	0.00983	0.98[†]
15–30 dollars	0.03157	0.03185	0.00028	0.03[†]
Above 30 dollars	0.19966	0.18688	− 0.01278	− 1.28
None	0.02692	0.02959	0.00267	0.27[†]
Indicator 2: Unable to eat healthy food				
No	0.50048	–	–	–
Yes	0.49952	**1 ***	–	–
Produced enough food				
No	0.39478	0.47903	0.08425	8.43[†]
Yes	0.60522	0.52097	− 0.08425	− 8.42
Ability to buy food				
No	0.60284	0.63221	0.02937	2.94[†]
Yes	0.39716	0.36779	− 0.02937	− 2.94
Total household income status				
Increased	0.19971	0.19754	− 0.00217	− 0.22
Reduced	0.42012	0.43488	0.01476	1.48[†]
Stayed the same	0.28414	0.26627	− 0.01787	− 1.79
No earnings	0.096034	0.10131	0.00528	0.53[†]
Ability to access food markets				
No	0.55875	0.57624	0.01749	1.75[†]
Yes	0.44125	0.42376	− 0.01749	− 1.75
Total value of assistance				
Below 15 dollars	0.67230	0.6677	− 0.00460	− 0.46
15–30 dollars	0.03207	0.02914	− 0.00293	− 0.29
Above 30 dollars	0.27598	0.26775	− 0.00823	− 0.82
None	0.02782	0.027189	0.00071	0.07[†]
Indictor 3: Ate few kinds of food				
No	0.52195	–	–	–
Yes	0.47805	**1 ***	–	–
Produced enough food				
No	0.39467	0.4643	0.06963	6.96[†]

Table 3 (continued)

Nodes and states	Initial state-beliefs[a]	New state-beliefs[b]	Changes in beliefs[c]	Percentage point change
Yes	0.60533	0.5357	-0.06963	-6.96
Ability to buy food				
No	0.60281	0.63441	0.0316	3.16[†]
Yes	0.39719	0.36559	− 0.0316	− 3.16
Total household income status				
Increased	0.19951	0.19134	− 0.00817	− 0.82
Reduced	0.41972	0.42267	0.00295	0.30[†]
Stayed the same	0.28444	0.27911	− 0.00533	− 0.53
No earnings	0.09632	0.10688	0.01056	1.06[†]
Total value of assistance				
Below 15 dollars	0.74008	0.73551	− 0.00457	− 0.46
15–30 dollars	0.031885	0.02898	− 0.00291	− 0.29
Above 30 dollars	0.20904	0.20058	− 0.00846	− 0.85
None	0.02647	0.02745	0.00098	0.10[†]
Household size				
1–4	0.23776	0.23180	− 0.00596	− 0.60
5–8	0.55070	0.54989	− 0.00081	− 0.08
Above 8	0.21154	0.21831	0.00677	0.68[†]
Indicator 4: Skipped a meal				
No	0.74763	–	–	–
Yes	0.25237	**1 ***	–	–
Produced enough food				
No	0.39647	0.52208	0.12561	12.56[†]
Yes	0.60353	0.47792	− 0.12561	− 12.56
Total value of assistance				
Below 15 dollars	0.63591	0.6875	0.05159	5.16[†]
15–30 dollars	0.03112	0.0413	0.01018	1.02[†]
Above 30 dollars	0.30495	0.2374	− 0.06755	− 6.76
None	0.02802	0.0338	0.00578	0.58[†]
Ability to buy food				
No	0.60279	0.65966	0.05687	5.69[†]
Yes	0.39721	0.34034	− 0.05687	− 5.69
Total household income status				
Increased	0.20281	0.1997	− 0.00311	− 0.31
Reduced	0.4199	0.42059	0.00069	0.07[†]
Stayed the same	0.2840	0.25035	− 0.03365	− 3.37
No earnings	0.0963	0.12626	0.02996	3.00[†]
Ability to stock enough food				
No	0.31677	0.35267	0.0359	3.59[†]
Yes	0.68323	0.64733	− 0.0359	− 3.59
Indicator 5: Ate less food				
No	0.6789	–	–	–
Yes	0.3211	**1 ***	–	–
Produced enough food				
No	0.39795	0.51438	0.11643	11.64[†]
Yes	0.60205	0.48562	− 0.11643	− 11.64
Ability to buy food				
No	0.60282	0.66224	0.05942	5.94[†]
Yes	0.39718	0.33776	− 0.05942	− 5.94

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Table 3 (continued)

Nodes and states	Initial state-beliefs[a]	New state-beliefs[b]	Changes in beliefs[c]	Percentage point change
Total household income status				
Increased	0.19941	0.19153	− 0.00788	− 0.79
Reduced	0.42053	0.42702	0.00649	0.65[†]
Stayed the same	0.28372	0.26153	− 0.02219	− 2.22
No earnings	0.096337	0.11992	0.02358	2.36[†]
Total value of assistance				
Below 15 dollars	0.61671	0.63117	0.01446	1.45[†]
15–30 dollars	0.030917	0.03387	0.00295	0.30[†]
Above 30 dollars	0.32389	0.30038	− 0.02351	− 2.35
None	0.028483	0.03459	0.00611	0.61[†]
Ability to access food markets				
No	0.55944	0.58448	0.02504	2.50[†]
Yes	0.44056	0.41552	− 0.02504	− 2.50
Indicator 6: Ran out of food				
No	0.81882	–	–	–
Yes	0.18118	**1 ***	–	–
Produced enough food				
No	0.39431	0.49087	0.09656	9.66[†]
Yes	0.60569	0.50913	− 0.09656	− 9.66
Total value of assistance				
Below 15 dollars	0.72697	0.75899	0.03202	3.20[†]
15–30 dollars	0.03249	0.05302	0.02053	2.05[†]
Above 30 dollars	0.20710	0.15541	− 0.05169	− 5.17
None	0.03258	0.03353	0.00095	0.09[†]
Total household income status				
Increased	0.20984	0.19989	− 0.00995	− 0.99
Reduced	0.40563	0.41977	0.01414	1.41[†]
Stayed the same	0.28410	0.24351	− 0.04059	− 4.06
No earnings	0.09623	0.14102	0.04479	4.48[†]
Ability to buy food				
No	0.60287	0.67042	0.06755	6.76[†]
Yes	0.39713	0.32958	− 0.06755	− 6.76
Sex of household head				
Female	0.31011	0.35081	0.0407	4.07[†]
Male	0.68989	0.64919	− 0.0407	− 4.07
Indicator 7: Nothing to eat (Went hungry)				
No	0.80398	–	–	–
Yes	0.19602	**1 ***	–	–
Produced enough food				
No	0.39452	0.4995	0.10498	10.50[†]
Yes	0.60548	0.5005	-0.10498	-10.50
Total value of assistance				
Below 15 dollars	0.72549	0.75777	0.03228	3.23[†]
15–30 dollars	0.03171	0.04526	0.01355	1.36[†]
Above 30 dollars	0.21651	0.15687	− 0.05964	− 5.96
None	0.02629	0.04009	0.0138	1.38[†]
Total household income status				
Increased	0.21583	0.19982	− 0.01601	− 1.60
Reduced	0.41106	0.41995	0.00889	0.89[†]

Table 3 (continued)

Nodes and states	Initial state-beliefs[a]	New state-beliefs[b]	Changes in beliefs[c]	Percentage point change
Stayed the same	0.28387	0.24193	− 0.04194	− 4.19
No earnings	0.09636	0.13118	0.03482	3.48[†]
Ability to buy food				
No	0.60286	0.66915	0.06629	6.63[†]
Yes	0.39714	0.33085	− 0.06629	− 6.63
Ability to stock enough food				
No	0.31681	0.37415	0.05734	5.73[†]
Yes	0.68320	0.62585	− 0.05735	− 5.74
Indicator 8: Went without food for a whole day				
No	0.90298	–	–	–
Yes	0.09702	**1 ***	–	–
Total value of assistance				
Below 15 dollars	0.63703	0.71483	0.0778	7.78[†]
15–30 dollars	0.03427	0.08120	0.04693	4.69[†]
Above 30 dollars	0.23735	0.13238	− 0.10497	− 10.50
None	0.07159	0.09135	0.01976	1.98[†]
Ability to stock enough food				
No	0.31673	0.44797	0.13124	13.12[†]
Yes	0.68327	0.55203	− 0.13124	− 13.12
Total household income				
Increased	0.22186	0.20020	− 0.02166	− 2.17
Reduced	0.35495	0.41914	0.06419	6.42[†]
Stayed the same	0.28419	0.24747	− 0.03672	− 3.67
No earnings	0.09648	0.17572	0.07924	7.92[†]
Produced enough food				
No	0.39263	0.50634	0.11371	11.37[†]
Yes	0.60737	0.49366	− 0.11371	− 11.37
Location of residence				
Rural	0.74199	0.66636	− 0.07563	− 7.56
Urban	0.25801	0.33364	0.07563	7.56[†]

[a] Represents the initial state belief probabilities of each determinant in the compiled BBN models shown in Fig. 3.and Additional file: Fig. S1–Fig. S7

[b] Reflects new state belief probabilities when the 'Yes' state belief finding in the food insecurity indicator nodes of the BBN models were tagged to probability of 1

[c] Indicates changes in probabilities from the initial to new state-beliefs

[*] the 'Yes' state of each outcome variable (i.e. Food insecurity indicator) was tagged to the probability of 1 to estimate the contribution of the selected determinant on food insecurity

[†] Represents the actual determinants and their positive contribution to each food insecurity indicator

assistance during the lockdown by the Government, the distributed food items were of poor quality, and were not sufficient to cater for the entire lockdown period. However, this result, and observation is contrary to an earlier study done in Uganda, which showed that urban households suffered less incidences of food insecurity compared to the rural ones, due to their multiple sources of income, and the high ownership of non-farm businesses [17]. The difference in results could be attributed to the modelling approaches used, the sample size, and the time when the data were collected.

Discussion

The strict implementation of COVID-19 stringent containment measures in Uganda led to widespread unemployment, loss of income, and low purchasing power, all of which affected all the four dimensions of food security, namely: availability, access, utilization, and stability [8]. These measures also exacerbated the pre-existing food insecurity vulnerabilities as well [17]. Although there have been attempts to model HFI during the COVID-19 lockdown in Uganda [8, 17], and other developing countries [9], these studies have primarily utilised traditional

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statistical models, including logistic and probit regression models, which are not able to fully capture the uncertainty, complexity, nonlinearity, and multidimensionality that were associated with the determinants of HFI that came up during the lockdown. Although these models have been useful in specific food insecurity settings, they have provided inconsistent results with limited applicability in decision making process [9, 14, 15, 40].

For the first time, this study has presented a probabilistic BBN modelling approach as a potential method to address the scientific uncertainty, interconnectedness, stochastic, and nonlinearity of the determinants of HFI during the entire lockdown in Uganda. The graphical BBN models developed in this study illustrate the complex interactions, organize and summarize the results in a visually appealing, and easy-to-understand format (Fig. 3 and Additional file 1: Fig. S1, Additional file 2: Fig. S2, Additional file 3: Fig. S3, Additional file 4: Fig. S4, Additional file 5: Fig. S5, Additional file 6: Fig. S6 and Additional file 7: Fig. S7). This novel modeling framework has the potential to be used as a decision support tool in efforts geared to reduce hunger, malnutrition, and to study food, and nutritional security, taking into consideration the complex causal relationships involved. Gaining a better understanding of how the pandemic has impacted HFI, and the pathways through which food insecurity occurred, is crucial for future food security assessments, and identification of food needs. It is also helpful in prioritization of interventions, and responses, particularly under the accelerating occurrence of pandemics, and environmental mediated stresses, shocks as well as disasters.

The developed BBN models were highly accurate, and were used to determine the prevalence of HFI in Uganda (Fig. 6). In this study, the status of the food insecurity indicators during the pandemic were comprehensively tracked using nationally representative data sets from the HFPS. Based on the interactions of different determinants in the developed BBN models (Fig. 3 and Additional file 1: Fig. S1, Additional file 2: Fig. S2, Additional file 3: Fig. S3, Additional file 4: Fig. S4, Additional file 5: Fig. S5, Additional file 6: Fig. S6 and Additional file 7: Fig. S7.), and the average of the posterior probabilities of the individual food insecurity indicators in Fig. 6, it can be concluded that 30.6% of the sampled households in Uganda were food insecure during the COVID-19 lockdown. A previous rapid assessment study done in Uganda involving 442 respondents during the initial stages of the pandemic also indicated a 44% increase in the number of food-insecure respondents [8]. These results are not surprising, as the pandemic greatly affected the resilience of local food systems [43], and the ability of households to respond to food insecurity challenges [39]. Thus, gaining

a clear understanding of resilience of local food systems, and households in Uganda, may aid in better programming of interventions to mitigate the negative effects of any recurring, and unanticipated pandemic, environmental change or socio-economic shocks.

In this study, the determinants of HFI during the lockdown were ranked in their order of importance (Fig. 7), rather than solely based on statistical significance using the traditional statistical models. Ranking, and prioritising the determinants of HFI are crucial as they help to allocate resources for targeted interventions within the constraint of limited funding. In Fig. 7, the inability of households to produce enough food was ranked as the number 1 determinant affecting all of the food insecurity indicators; consequently, this should be a key focus of intervention. Agricultural production in Uganda is affected by various impediments including inadequate support in terms of training, market, and subsidies for the genuine agricultural inputs, limited land, infertile soils, and land degradation among others. All these challenges have prompted many Ugandans to leave agriculture and engage in other businesses [28]. This is exacerbated by the rising service sector in the country, amidst a growing youth population with limited interest in agriculture. This shift in workforce, and focus, is a big threat to the food security situation in Uganda, and need immediate attention. All the indicators of food insecurity can be addressed when organic farming is promoted. Studies have shown that organic farming can reduce drastically HFI, can protect the environment, can increase farmers' income, reduce external input costs, enhance social capacity, increase employment opportunities, and it is highly resilient to environmental changes [55, 56].

Conclusion

The BBN models in this study are valuable for visualizing the inference results, which can effectively be used for hypothesis generation and decision-making processes regarding interventions for food insecurity. Based on the interactions observed among different determinants in the developed BBN models, it can be concluded that, during the COVID-19 lockdown, 30.6% of the sampled households in Uganda were food insure. Notably, the determinants of HFI during the lockdown were ranked based on their importance rather than their statistical significance, as is typically the case with the traditional statistical models. The top five ranked determinants of HFI were identified as follows: (1) households' inability to produce enough food; (2) inability to purchase food; (3) reduced household income, (4) limited cash assistance, and (5) insufficient food stockpiling. Interventions targeting the most crucial determinants of HFI identified through this ranking will be instrumental in enhancing

the resilience of local food systems and households' capacity to cope with recurring and unforeseen shocks. One major strength of this study lies in its utilization of a novel BBN modeling approach, leveraging nationally representative and repeated phone survey data to generate new evidence on the determinants of HFI throughout the entire lockdown period in Uganda. As a result, these findings can be extrapolated to gain a deeper understanding of HFI determinants in Uganda, and other countries with similar demographic and socioeconomic contexts.

However, it is important to acknowledge some limitations of this study. First, environmental and climate factors, which may also influenced food insecurity during lockdowns, were not included in the analysis. Second, while its was acknowledge that the data sets used in our analysis were nationally representative, it is worth noting that phone surveys are susceptible to various forms of selection biases, including coverage bias, non-response bias, and respondent preference bias [57]. Third, the spatial component is missing in this study, as the data sets used lacked the spatially disaggregated regional, and district specific data. Fourth, the data sets used lacked information on specific socio-economic groups, and as a result, this study was not able to determine the food insecurity situations among these groups. Despite these limitations, our study was sufficiently powered by the BBN modeling approach to rank several determinants of food insecurity that should be prioritized in Uganda. Looking ahead, the BBN models can be further developed into more complex, dynamic spatial models that incorporate temporal and spatial environmental data. Such advancements would yield results beneficial for targeted food insecurity interventions at a regional scale.

Abbreviations

BBN	Bayesian belief network
COVID-19	Coronavirus disease 2019
FAO	Food and Agriculture organisation
HFI	Household food insecurity
FIES	Food insecurity experience scale
SARS-CoV-2	Severe acute respiratory syndrome coronavirus-2
NGO	Non-governmental organizations
SSA	Sub-Saharan Africa
SDG	Sustainable Development Goal
HFPS	High-Frequency Phone Surveys
WHO	World Health Organization

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40066-023-00460-2.

Additional file 1: **Fig. S1.** BBN model depicting the interaction among the determinants of food insecurity indicator 2 (i.e. Unable to eat health food).

Additional file 2: **Fig. S2.** BBN model depicting the interaction among the determinants of food insecurity indicator 3 (i.e. Ate few kinds of food).

Additional file 3: **Fig. S3.** BBN model depicting the interaction among the determinants of food insecurity indicator 4 (i.e. Skipped a meal).

Additional file 4: **Fig. S4.** BBN model depicting the interaction among the determinants of food insecurity indicator 5 (i.e. Skipped a meal).

Additional file 5: **Fig. S5.** BBN model depicting the interaction among the determinants of food insecurity indicator 6 (i.e. Ran out of food).

Additional file 6: **Fig. S6.** BBN model depicting the interaction among the determinants of food insecurity indicator 7 (i.e. Nothing to eat).

Additional file 7: **Fig. S7.** BBN model depicting the interaction among the determinants of food insecurity indicator 8 (i.e. went without food for a whole day).

Additional file 8: **Table S1.** Sensitivity analysis of 'Not having enough food to eat' to a finding at another node.

Additional file 9: **Table S2**. Sensitivity analysis of 'Unable to eat healthy food' to a finding at another node.

Additional file 10: **Table S3**. Sensitivity analysis of 'Ate few kinds of food' to a finding at another node.

Additional file 11: **Table S4.** Sensitivity analysis of 'Skipped a meal' to a finding at another node.

Additional file 12: **Table S5.** Sensitivity analysis of 'Ate less food' to a finding at another node.

Additional file 13: **Table S6**. Sensitivity analysis of 'Ran out of food' to a finding at another node.

Additional file: 14: **Table S7**. Sensitivity analysis of 'Nothing to eat (Went hungry)' to a finding at another node.

Additional file 15: **Table S8**. Sensitivity analysis of 'Went without food for a whole day' to a finding at another node.

Additional file 16: **Table S9.** Importance ranking of the determinants across the eight food insecurity indicators.

Author contributions

HMS contributed to conceptualisation, methodology, data acquisition, literature review, formal analysis, visualisation, validation, preparation, editing of the original draft and made all the necessary revisions. SL participated in conceptualisation, literature review, methodology, model validation, editing of original draft and revisions. SLM, contributed to the conceptualisation, editing of the original draft, proof reading, language editing, and all the necessary revisions. PIM, FM, DN, HW, PK, ASP, PW and JN contributed to the project administration, conceptualisation, editing of the manuscript and revisions. All authors reviewed the draft and approved the final submission for publication.

Availability of data and materials

The data used in this study can be obtained by sending a request via the World Bank Microdata Library website and upon approval, data can be obtained from https://microdata.worldbank.org/index.php/catalog/3765/data-dictionary/F82?file_name=SEC5B.

Declarations

Ethics approval and consent to participate

This study was conducted in accordance with the ethical principles stated in the Helsinki Declaration. During data collection, the informed consent of eligible respondents was sought before starting the interviews. The datasets used was fully anonymised.

Author details
[1]Department of Geography, Geo-Informatics and Climatic Sciences, Makerere University, P. O Box 7062, Kampala, Uganda. [2]Department of Environmental and Global Health, College of Public Health and Health Professions, University of Florida, 2055 Mowry Rd, Gainesville, FL 32610, USA. [3]Department of Environmental Health Sciences, School of Public Health & Health Sciences, University of Massachusetts, Amherst 01003, USA. [4]Center for African Studies, University of Florida, Gainesville, FL 32611, USA. [5]National Environmental Management Authority (NEMA), Plot 17/19/21 Jinja Road, P.O. Box 22255, Kampala, Uganda. [6]Department of Horticulture and Food Security, Jomo Kenyatta University of Agriculture and Technology, P.O. Box 62, Nairobi 00200, Kenya.

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