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The impact of social welfare and COVID-19 stringency on the perceived utility of food apps: A hybrid MCDM approach

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ABSTRACT

The COVID-19 pandemic has created enormous challenges for society due to the various ways of impacting health. This paper focuses on the impact of the COVID-19 pandemic on people’s food consumption patterns in the online environment. We investigate food app reviews and examine whether countries with a high rate of success with COVID-19 control consume more unhealthy food through mobile apps. We also investigate whether the population of countries with low social welfare eat more unhealthy food during the COVID-19 pandemic compared to countries with high social welfare. We take a hybrid multi-criteria decision making (MCDM) approach to calculate indexes based on the technique for order of preference by similarity to an ideal solution, complex proportional assessment, and VlseKriterijuska Optimizacija I Komoromisno Resenje. Results show that country social welfare and success in COVID-19 control negatively affect the perceived utility of the apps. Also, success in COVID-19 control and the perceived utility of food apps positively affect the proportion of unhealthy reviews, whereas social welfare has a negative impact. The results have important implications for public health policymakers, showing that the online food environment can be an important setting for interventions that seek to incentivize healthy eating.

1. Introduction

Amid the global spread of COVID-19, governments worldwide have implemented a wide range of responses to contain the spread of the virus. Efforts to curb viral transmission include school and workplace closures, cancellation of public events, restrictions on gatherings, mask mandates, and stay-at-home requirements. In the absence of effective vaccines or medicine to treat COVID-19, such government policies are aimed at protecting residents against exposure to the virus. However, at the same time, these policies seek to benefit public health. Moreover, research has recently shown that such policies are associated with important social and environmental changes, which can in turn influence health-related behaviors [1].

Since restrictive policies were implemented by local governments everywhere, hospitality has been one of the most affected sectors, and many food chains, restaurants, and bars have been forced to readapt and shift their entire service [2]. The pandemic demanded new forms of relating to food, both from retailers and from consumers. Therefore, we observe an enormous increase in the demand for online food retailing [3]. However, little do we know about the impact such transformation has had on individual food consumption patterns, especially on the consumption of unhealthy foods. Thus, this study aims to understand the relationship between COVID-19 control and the consumption of unhealthy food through mobile apps.

To compare and track COVID-19 health response policies around the globe, the Oxford COVID-19 Government Response Tracker (OxCGRT) project developed a tool that systematically gathers information on several different policy responses undertaken by governments since the outbreak began [4]. Accordingly, the stringency index relies on publicly available data on eight different indicators that are aggregated to create a stringency score ranging from 0 to 100. The index reflects the strictness of the policy response and enables researchers and public authorities alike to track government actions over time and across countries. We rely on the OxCGRT stringency index, as well as the number of cases and deaths by population to create the COVID-19 control success index.

We also use secondary data from the Google App Store and treated...
the data by observing reviews about unhealthy (ultra-processed food products) and healthy food (unprocessed and minimally processed foods, that is, foods make without industry methods and techniques “to turn whole fresh foods into food products” [5]). We investigate the impact of success with COVID-19 control on individual food consumption patterns in the online environment in 17 countries. We analyze food app reviews from January 2020 to March 2021 and examine whether countries with high success in COVID-19 control consume more unhealthy food through mobile apps.

We also investigate whether the populations of countries with low social welfare eat more unhealthy food during the COVID-19 pandemic, compared with countries with high social welfare. Individuals' social welfare can be defined as [6] “a state or condition of human well-being,” which can also include the concepts of contentment or fulfillment. Studies analyzing the social welfare of countries, consider it as a multidimensional concept that may include per capita income, income distribution, employment, economic situation, social security, health, education, housing, etc. [7]. Furthermore, this study explores the effect of countries’ social welfare and success with COVID-19 control on the perceived utility of food apps, as well as the relationship of food apps with unhealthy food consumption. According to [8], in the e-commerce setting, utility includes product offerings, product information, monetary savings, and convenience.

We take a hybrid multi-criteria decision making (MCDM) approach to evaluate the antecedents of food app perceived utility and unhealthy food consumption. First, we calculate the countries’ social welfare index, in which we employ a technique for order of preference by similarity to ideal solution (TOPSIS) to consider it as an ideal solution of social condition, positively related to GDP (gross domestic product), HDI (human development index), life expectancy, and hospital beds per 1000, and negatively related to inflation. Second, we calculate the success rate index for COVID-19 control by employing VisleKriterijuska Optimizacija I Komoromisno Resenje (VIKOR) to measure the tradeoff of the positively related country-wide policy stringency and the negatively related number of cases and deaths by population. Third, we calculate food app perceived utility, in which we employ complex proportional assessment (COPRAS) to measure the utility to the user, including positively related variables (rating, number of reviewers and installs) and negatively related variables (advertisements and size).

We used these three indexes to understand the factors that influence unhealthy consumption. Social distancing is one of the critical factors related to the success of COVID-19 control [9]. However, psychological distance is related to social anxiety [10], which in turn, is related to unhealthy eating behaviors [11,12]. Thus, we argue that the success of COVID-19 control may positively influence unhealthy food consumption. However, countries with low social welfare may have greater unhealthy food consumption, since poverty is related to unhealthy behaviors [13]. Moreover, the perceived utility of food apps may influence unhealthy food consumption since the previous literature indicates that the online food environment offers a high proportion of ultra-processed and unhealthy food and this can hamper healthy eating, especially during the pandemic [14,15].

The findings of this study have both theoretical and practical importance. We build on the literature relating to the COVID-19 pandemic and food consumption by showing the increase of unhealthy food in the online environment and by answering a recent call to investigate “the effect of the pandemic on dietary diversity or nutritional status of individuals or households” [16].

2. Literature review

This study combines a largely explored concept – social welfare – with topics that arose more recently – mobile apps and COVID-19 control. In this section, we dig into the literature to explore what scholars have proposed in these three fields. We searched Google Scholar for articles that employed the terms “social welfare,” “success of COVID-19 control,” and “utility app.” We then selected the articles that had the best fit with our purpose – to investigate the relationships among (a) country social welfare, success in COVID-19 control, perceived utility of apps and (b) unhealthy food consumption.

Social welfare has been the subject of studies for many decades (e.g., [17]). More recently [18], presented a welfare-based analysis of fair classification regimes based on machine learning algorithms, and [19] studied the voluntary adoption of social welfare-enhancing behavior. Moreover [20], applied a survey to rank capabilities (i.e., health, social relations, and financial situation) for the Swedish context, which supports the continued development of capability-adjusted life years for monitoring and evaluating outcomes in social-welfare interventions.

The impact of the mobile phone on society is tremendous. Mobile has been responsible for the explosion of the use of information and communication technologies (ICTs) in developing countries and has impacted lives around the world, with effects “particularly striking in poorer communities and countries in which ICTs have previously been less common” [21]. In the last decade, mobile apps have emerged as an important field of research and have become extremely important in the digital transformation process of companies. As [22] argued, the use of digital technologies such as mobile fuels disruptions since it increases the availability of data and enables changes in value creation paths (e.g., digital channels).

Consequently, the utility of apps has been largely explored, although most of the studies aim to access the usability of specific apps using qualitative approaches and surveys. For instance [23], explore the utility of an existing mental health app through group discussions and surveys [24], examine the usability and inter-rater reliability of an app for the System for Observing Play and Recreation in Communities using observers to collect data [25]. describe the usability and utility testing of a newly developed medication adherence app among ambulatory care patients in Malaysia employing beta testing and in-depth interviews. A broad literature examining food apps has focused on their functionalities and their relationship with customers [26]. analyzed the scope, characteristics, and quality of food and nutrition apps [27]. investigated whether nutrition-information apps influence consumers’ consumption of healthy food by interviewing them [28]. assessed the feasibility and appeal of apps that promote healthy food among socio-economically disadvantaged women [29]. examined the psychological factors that influence the adoption of smartphone diet apps by restaurant customers.

Scholars studying the digital food environment during the pandemic have argued that there has been more advertising of unhealthy than healthy food. For instance, during the 13th and 14th weeks of the pandemic, advertisements published in an online food delivery platform in Brazil focused more on unhealthy food items [15]. Also, fast-food brands were most likely to use COVID-19 themed posts in New Zealand [30].

Studies related to COVID-19 control have shown that effective communication, social distancing, uptake of new technology, modifying the rules and regulation at the workplace, sealing national borders, and strong leadership and government control are critical success factors as preventive measures to control the pandemic [9]. Moreover, it was shown that the rapid response in introducing stay-at-home orders is important to reduce the impacts of COVID-19 [31], and case isolation and effective contact tracing can, within three months, control an outbreak of COVID-19 [32]. Additionally, high-q facilities, comprehensive COVID-19 testing policies, strict lockdown measures, penalties, and high level of trust towards the government seemed to be significant in determining the severity of COVID-19 severity [33].

COVID-19 and COVID-19 responses have an enormous effect on social welfare [34,35]. Thus, governments have created policies to try to diminish these threats [36]. In India, a democratic local government was able to build a network of trust through cooperation with state actors to implement state responses to the pandemic [37]. Importantly, it is also important to set up a national committee to combat the pandemic’s...
The COVID-19 pandemic had an impact on health in different ways. Several studies have shown that the COVID-19 pandemic has caused anxiety [39–41]. More specifically, psychological distance mediates the relationship between COVID-19 pandemic severity and social anxiety [10]. There is also evidence that anxiety affects unhealthy eating behaviors [11,12]. Consequently, some studies started to investigate the impact of the pandemic on unhealthy eating behaviors (e.g., [42]).

3. Hypotheses development

The COVID-19 pandemic had an impact on health in different ways. Several studies have shown that the COVID-19 pandemic has caused anxiety [39–41]. More specifically, psychological distance mediates the relationship between COVID-19 pandemic severity and social anxiety [10]. There is also evidence that anxiety affects unhealthy eating behaviors [11,12]. Consequently, some studies started to investigate the impact of the pandemic on unhealthy eating behaviors (e.g., [42]).

3.1. Antecedents of perceived utility of food apps

Countries with low social welfare such as the Philippines, Brazil, and Colombia have a population that spends more time online [43]. In addition, countries with low social welfare spent more time with social media, thus, the Philippines, Nigeria, and India are the countries with the highest time spent connected to social networks [44]. Because the populations of low social welfare countries give more value to the online environment, it is plausible to argue that they also will also value consumption of mobile apps to a greater extent. Therefore, we hypothesize the following effect:

**H1a.** Country social welfare negatively affects the perceived utility of

### Table 1

| Authors | Research question | Methods | Conclusion |
|---------|-------------------|---------|------------|
| [18]    | How do leading notions of fairness as defined by computer scientists map onto longer-standing notions of social welfare? | Machine learning algorithms | Always preferring fairer classifiers does not abide by the Pareto Principle—a fundamental axion of social choice theory and welfare economics. |
| [20]    | How to rank capabilities and suggest a relevant set of capabilities for the Swedish context to inform the development of capability-adjusted life years. | Survey | Health, social relations, and financial situation were the most important capabilities. |
| [19]    | Identify the barriers to mask-wearing in Spain | Survey | Young, educated, unconcerned with being infected, and an introverted personality—the typical profile of citizens resistant to face-masking. |
| [23]    | Explore the utility of an existing mental health app within an apprentice population and evaluate the usability, acceptability, feasibility, and preliminary efficacy of a modified version of the app. | Group discussions and survey | The app was a well-received intervention when adapted to young apprentices. |
| [24]    | Examine the usability and inter-rater reliability of an app for the System for Observing Play and Recreation in Communities (ISOPARC®). | Observation | ISOPARC® can be used reliably for examining variables previously validated in System for Observing Play and Recreation in Communities. |
| [25]    | Describe the usability and utility testing of a newly developed medication adherence app—Med Assist—among ambulatory care patients in Malaysia. | Beta testing and in-depth interviews | The usability and utility testing of Med Assist with end-users made the app more patient-centered in ambulatory care. |
| [26]    | Understand the scope, characteristics, and quality of food and nutrition apps. | Reviewers evaluated the apps | Food choice and family organizer apps scored highest for app quality, whereas most apps scored well for functionality and poorly for engagement. |
| [27]    | Whether nutrition-information apps influence consumption of healthy food. | Interview | Nutrition-information apps can be effective in overcoming what consumers perceive as personal limitations in approaching healthy food. |
| Mouchacca, & Jackson (2014) | Understand the feasibility and appeal of apps that promote healthy food among socioeconomically disadvantaged women. | Survey | Selected apps are usable and appealing to socioeconomically disadvantaged women. |
| [29]    | What are the psychological factors that influence customers’ intention to use such apps when ordering food at restaurants? | Survey | Customers’ intention to use smartphone diet apps is predicted by the performance of the application, anticipated effort of usage, social influence, and degree of user innovativeness. |
| [9]     | Which strategy can balance both preventive measures and economic losses to control the pandemic? | Decision-making trial and evaluation laboratory (DEMATEL) | The six critical success factors identified are “Effective communication,” “Social distancing,” “Adopting new technology,” “Modify the rules and regulation at the workplace,” “Sealing the borders of the territory” and “Strong leadership and government control.” |
| [31]    | Investigate the sensitivity of COVID-19’s outcomes to variations in the timing of the interventions. | Stochastic branching process model | The rapid response in introducing stay-at-home orders was crucial in reducing the number of cases and deaths and increasing the probability of elimination. |
| [32]    | Are isolation and contact tracing able to control onwards transmission from imported cases of COVID-19? | Stochastic transmission model | Highly effective contact tracing and case isolation are enough to control a new outbreak of COVID-19 within 3 months. |
| [37]    | How are state authorities attempting to bridge the gap between the need for a rapid, vigorous response to the pandemic and local realities in three Indian states (Rajasthan, Odisha, and Kerala)? | Interviews | Kerala’s long-term investment in democratic local government and arrangements for incorporating women within grassroots state functions have built a high degree of public trust and cooperation with state actors, while local authorities embrace an ethic of care in the implementation of state responses. |
| [33]    | What and how the multifaceted social, physical, and governance factors affected the success level of seven selected Asia-Pacific countries (South Korea, Japan, Malaysia, Singapore, Vietnam, Indonesia, and New Zealand) in combating COVID-19? | Content analysis | High facility adequacy, comprehensive COVID-19 testing policies, strict lockdown measures, penalties, and high level of trust towards the government seemed to be significant in determining the COVID-19 severity in a country. |
During the COVID-19 pandemic, food apps were an important tool to avoid contact with others [45]. Furthermore, social isolation has a positive impact on the intention to use food apps [46]. However, the fast rise in user numbers may impose several challenges for the food app, since the company needs to be available within the shortest possible time to address customers’ orders and complaints [45]. Thus, the rapid rise of users in countries with more restrictions may affect the satisfaction and the value created by the app. Accordingly, we arrive at the following hypothesis:

\[ H1b. \text{ The success of COVID-19 control negatively affects the perceived utility of food apps.} \]

\section*{3.2. Antecedents of unhealthy food consumption}

Social distancing is one of the critical factors related to the success of COVID-19 control [9]. However, psychological distance is related to social anxiety [10], which in turn, is related to unhealthy eating behaviors [11,12]. Thus, we argue that the success of COVID-19 control may influence unhealthy food consumption and arrive at the following hypothesis:

\[ H2a. \text{ The success of COVID-19 control positively affects the proportion of unhealthy reviews.} \]

Apps and websites have been an important driver for (un)healthy food consumption in the food environment literature (Downs et al., 2020). The online food environment offers a high proportion of ultra-processed and unhealthy food, which can hamper healthy food eating, especially during the pandemic [14,15]. Thus, we hypothesize that:

\[ H2b. \text{ The perceived utility of food apps positively affects the proportion of unhealthy reviews.} \]

Individuals from countries with low social welfare may consume unhealthy food at a higher rate, since poverty is related to unhealthy behaviors [13]. With that, we arrive at another effect:

\[ H2c. \text{ Country social welfare negatively affects the proportion of unhealthy reviews.} \]

\section*{4. Data and methodology}

\subsection*{4.1. Data}

We collected data from the Google Play Store from 17 countries (Austria, Brazil, Canada, France, Germany, India, Italy, Japan, Netherlands, Poland, Russia, Singapore, Sweden, Switzerland, Ukraine, United Kingdom, United States). Following [47]; our sample of countries includes major mature (e.g., the United States, Germany) and emerging (e.g., Brazil, India, Russia) markets with a wide variety of cultural and economic characteristics. The app store contains both local and global apps. As it shows the apps available according to the user location, we used a VPN to simulate each user location and download all available app ids that were later used in the web scraper to collect the reviews from the category ‘Food and Drinks’ of Google Play Store. We collected data from December 2, 2020, to March 10, 2021, from 275 apps. We provide the list of app ids in the supplementary materials of the Journal. The app id is what Google Play Store uses at the end of a URL. For instance, the app id of Burger King France is the first app id on the list and the app can be accessed by placing the id after “https://play.google.com/store/apps/details?id=” as follows: https://play.google.com/store/apps/details?id=air.com.unit9.bkFrApp.

The apps stores provide reviews going back many years. However, since we are interested in the impact of the COVID-19 pandemic, we only use data from January 1, 2020. We filtered the reviews of apps that take into account the extent and purpose of food processing, that is, “methods and techniques used by the food, drink, and associated industries to turn whole fresh foods into food products” [5]. We created a list with the translation for the languages of the researched countries, totaling 297 terms of unhealthy food and 1147 terms of healthy food based on previous works [5,48,49]. We also collected, from the Google Play Store, some information about the apps that were used to create the app utility index: rating, the number of reviewers and installs, whether there are advertisements, and size of the app.

We collected the Human Development Index (HDI) from United Nations (http://hdr.undp.org/en); Gross Domestic Product (GDP), life expectancy, inflation, and hospital beds per 1000 from World Bank (https://data.worldbank.org/); and total cases/population, new cases/population, total deaths/population, new deaths/population from Our World in Data (https://ourworldindata.org/).

To measure a country’s policy stringency, we collected workplace-closing data from OxCGRT (https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker). (See [50] for a more detailed description.) Briefly, the dataset relies on official data on public policy measures adopted by governments to deal with COVID-19, including school and workplace closings, restriction on public events and private gatherings, public transport closing, stay-at-home requirements, restriction on international travel, and other government responses. The OxCGRT assigns a score for each of these indicators according to its level of strictness, with higher numbers indicating greater stringency [50]. We considered the workplace closing indicator – which includes government action to close bars and restaurants – because this is a restriction that happened in many countries. Moreover, we assume that workplace closing is the measure that most influences online eating behavior. Fig. 2 shows the average workplace closing stringency scores over time for the 17 countries of our sample.

\subsection*{4.2. Methodology}

To measure social welfare, the success of COVID-19 control, and the perceived utility of food apps, we calculate three indexes:

1. social welfare index, which is positively related to GDP, HDI, life expectancy, and hospital beds per 1000, and negatively related to inflation; we employ TOPSIS to assess the index as an ideal solution of social condition.

2. success index of COVID-19 control, employing VIKOR to measure the tradeoff of a country’s policy stringency, which is positively related, versus total cases/population, new cases/population, new deaths/population, total deaths/population, new deaths/population from Our World in Data (https://ourworldindata.org/).

Fig. 1 summarizes our hypotheses about the effect of successful COVID-19 control, perceived utility of food apps, and country social welfare on the proportion of unhealthy reviews.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Antecedents of the perceived utility of food apps and proportion of unhealthy foods.}
\end{figure}
total deaths/population, new deaths/population, which are negatively related.

(3) perceived utility of food apps index, which is positively related to ratings, the number of reviewers and installs, and negatively related to advertisements and size; we employed COPRAS to measure the utility to the user.

The relative weightings we assigned to VIKOR, TOPSIS, and COPRAS were based on the entropy of the variables. Since we have unbalanced data, with a different number of reviews for each country, weekdays, and months, we controlled for the influence of these variables. Thus, we aggregate countries and languages in higher levels (i.e., continent and English versus other languages) and used them as well as weekday and trend (month/year) as control variables to test each hypothesis.

Moreover, because the apps’ data are unbalanced and we have count data, we performed the Poisson regression with random effects \[51\] in the following models:

Model 1: \[\text{Utility} = f(\text{COVID}, \text{Welfare}, \text{Trend}, \text{Weekday}, \text{Language type, Continent})\]
Model 2: \[\text{Proportion of unhealthy reviews} = f(\text{Utility, COVID, Welfare, Trend, Weekday, Language Type, Continent}),\]

where Utility is the food apps perceived utility index; COVID is the index of COVID-19 control success; Welfare is the social welfare index; Trend is a categorical variable in which the first month (January 2020) takes 1, the second takes 2, etc.; Weekday is the day of the week on which the review was published; Language type is a dummy variable which takes value 1 when the content of the review is written in English and 0 otherwise; Continent indicates where the app is available; and Proportion of unhealthy reviews is the ratio of the number of reviews with unhealthy terms to the number of reviews with healthy terms.

We also perform a transfer entropy, which is a nonparametric measure of asymmetric information transfer between time series (Behrendt et al., 2019). Transfer entropy has been used to quantify information flows between financial markets \[52, 53\]. We follow \[54\] and calculate the transfer entropy based on the transfer entropy of \[55, 56\]. Next, we detail the three MCDM approaches and the calculation of transfer entropy employed in this study.

4.2.1. TOPSIS

TOPSIS is a technique that chooses the alternative with the shortest distance from the ideal solution and the farthest from the negative ideal solution (Hwang & Yoon, 1981). TOPSIS was applied in a two-stage method combined with the social welfare function to select potential third-party logistics suppliers \[57\]; TOPIS has also been combined with VIKOR to study sustainable development in the EU countries \[58\]. In the present study, we employ TOPSIS to assess the ideal solution for social welfare. The next lines explain the TOPSIS method.

Whereas the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria, the positive ideal solution maximizes the benefit criteria and minimizes the cost criteria \[59\]. As shown by \[60\]; the TOPSIS technique is built upon an evaluation matrix consisting of \(m\) alternatives and \(n\) criteria with the intersection of each option and criteria given as \(x_{ij}\). First, one obtains a matrix \((r_{ij})_{mn}\) which is first normalized from a regulated matrix \((r_{ij})_{mn}\) as demonstrated in Eq. (1).

\[
r_j = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad i = 1, 2, \ldots, m \quad \text{and} \quad j = 1, 2, \ldots, n
\]

![Fig. 2. Workplace-closing stringency scores by country over time.](image-url)
After normalization, the weighted normalized decision matrix for performance assessment is calculated, observing Eq. (2).

$$W = \{w_j\}_{max} = \{w_j r_{ij}\}_{max}$$

where $w_j$ is the weight given to the criteria $j$ and $\sum_{j=1}^{n} w_j = 1$.

Then, we determine the worst alternative (the negative ideal assessment unit) $A_w$ demonstrated in Eq. (3), and the best alternative (the positive ideal assessment unit) $A_b$ as shown in Eq. (4).

$$A_w = \{\min\{w_j i | 1, 2, \ldots, m\} j \in J_+ \} = \{a_{wj} | j = 1, 2, \ldots, n\}$$

$$A_b = \{\max\{w_j i | 1, 2, \ldots, m\} j \in J_+ \} = \{a_{bj} | j = 1, 2, \ldots, n\}$$

where $J_+ = \{j | j \in positive\}$ and $J_- = \{j | j \in negative\}$, which are a set of positive and negative attributes, respectively.

Next, we calculate the distance $d_a$ between the target alternative $i$ and the worst condition $A_w$, as demonstrated in Eq. (5).

$$d_a = \sqrt{\sum_{j=1}^{n} (w_j - a_{wj})^2}, i = 1, 2, \ldots, m$$

The distance $d_b$ between the alternative $i$ and the best condition $A_b$ is calculated, as demonstrated in Eq. (6).

$$d_b = \sqrt{\sum_{j=1}^{n} (w_j - a_{bj})^2}, i = 1, 2, \ldots, m$$

where $d_a$ and $d_b$ are the Euclidean distance from the target alternative $i$ to the worst and best conditions, respectively.

Further, we calculate the similarity of alternative $i$ to the worst condition (the inefficient best conditions).

$$S_i = d_a (d_a + d_b)$$

where $0 \leq S_i \leq 1, i = 1, 2, \ldots, m$

$S_i = 0$, if and only if the alternative solution has the worst condition.

$S_i = 1$, if and only if the alternative solution has the best condition.

Lastly, we rank the alternatives according to $S_i$, where a higher value of $S_i$ indicates a better solution concerning higher indicator levels.

4.2.2. VIKOR

VIKOR was introduced by [61] and has recently been employed to evaluate the safety levels of 100 regions in the world in terms of COVID-19 [62]. This has made it feasible to prioritize COVID-19 patients in the context of individual and group decision making [63], thereby evaluating and improving healthcare system quality [64]. The present study employs VIKOR to assess the success of COVID-19 control at the country level.

Like TOPSIS, VIKOR is based on an aggregating function representing closeness to the ideal and uses normalization to eliminate the units of criterion functions [65]. However, VIKOR determines a compromise solution, providing a maximum group utility for the majority and a minimum of an individual regret for the opponent. It starts with the form of Lp-metric as demonstrated in Eq. (7).

$$L_{p,j} = \left\{ \sum_{i=1}^{n} \left[ w_j (f_i^* - f_i) / (f_i^* - f_i^*) \right]^p \right\}^{1/p},$$

$1 \leq p \leq \infty; j = 1; 2, \ldots, J$

Within the VIKOR method $L_{1,j}$ (as $S_j$ in Eq. (9)) and $L_{\infty,j}$ (as $R_j$ in Eq. (10)) are used to formulate ranking measures. The solution obtained by $\min S_j$ is with a maximum group utility (majority rule), and the solution obtained by $\min R_j$ is with a minimum individual regret of the opponent.

The compromise solution $F^*$ is a feasible solution that is the closest to the ideal $F^*$, and compromise means an agreement established by mutual concessions, as shown in Eq. (8).

$$\Delta f_1 = f_1^* - f_i^* \quad \text{and} \quad \Delta f_2 = f_i^* - f_i^*$$

To create the compromise ranking algorithm, first the best $f_i^*$ and the worst $f_i^*$ values of all criterion functions are determined, $i = 1; 2, \ldots, n$. If the $i$th function represents a benefit, then:

$$f_i^* - \max f_i^* \ldots f_i^* - \min f_i^*$$

Next, we compute the values $S_j$ and $R_j; j = 1; 2, \ldots, J$, by the relations of Eqs. (9) and (10).

$$S_j = \frac{\sum_{i=1}^{n} w_i (f_i^* - f_i) / (f_i^* - f_i^*)}{n},$$

$$R_j = \max \{w_i (f_i^* - f_i) / (f_i^* - f_i^*)\}$$

where $w_i$ are the weights of criteria, expressing their relative importance. Further, we compute the values $Q_i; j = 1; 2, \ldots, J$, by the relation

$$Q_i = v (S_j - S^*) / (S^* - S^*) + (1 - v) (R_j - R^*) / (R^* - R^*)$$

where

$$S^* = \min S_j, \quad S^* = \max S_j,$$

$$R^* = \min R_j, \quad R^* = \max R_j,$$

and $v$ is introduced as the weight of the strategy of the majority of criteria (or the maximum group utility), here $v = 0.5$.

Next, we rank the alternatives, sorted by the values $S, R, Q$, in decreasing order. The results are three ranking lists. Then, we propose as a compromise solution the alternative ($a^*$) which is ranked the best by the measure $Q$.

4.2.3. COPRAS

COPRAS was introduced by [66] and, in the technology field, was employed to select the best mobile model among various alternatives available on the market [67] to select Cloud Computing Technology [68] and to select an optimal building technological project [69]. The present study applies COPRAS to assess the utility of food apps. In the next line, we explain the COPRAS method.

First, one creates a decision-making matrix $X$, containing $m$ criteria and $n$ alternatives, as demonstrated in Eq. (11).

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} i = 1, 2, \ldots, n; j = 1, 2, \ldots, m$$

Then, the decision matrix $X$ is normalized by computing:

$$\tilde{x}_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}}$$

Then, the decision matrix will be:

$$\tilde{X} = \begin{pmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{pmatrix}$$

Next, we compute the weighted normalized decision matrix employing:
L. Hassad de Andrade et al.

Therefore, \( P = \sum_{j=1}^{n} x^j \) (12)

Next, we sum up the smaller values that are more preferable, as shown in Eq. (13),

\[ R_i = \sum_{j=1}^{n} x^j \] (13)

Then, the number of criteria that should be minimized is given by the difference \( m - k \).

Further, we minimize \( R_i \) observing Eq. (14),

\[ R_{\text{min}} = \min_{i=1}^{n} R_i \] (14)

Next, we compute the relative significance of each alternative \( Q_i \) as given in Eq. (15).

\[ R_i = P_i + P_i \sum_{j=1}^{n} R_i \]

(15)

Further, we identify the optimal alternative \( i \), given by \( K \), as illustrated,

\[ K = \max_{i=1}^{n} Q_i \]

Next, we prioritize alternatives in descending order and determine the utility degree \( N_i \) of each subsequent alternative \( i \), given as:

\[ N_i = \frac{Q_i}{Q_{\text{max}}} \]

4.2.4. Transfer entropy

We followed [54] to estimate [55,56] transfer entropy. Shannon’s entropy (1948) shows that we can measure uncertainty by calculating the average number of bits required to optimally encode independent draws as:

\[ H_I = \sum_{j} p(j) \log_2 p(j) \]

in which \( J \) is a discrete random variable and \( p(j) \) is the probability distribution.

Next, we measure the information flow between two time series. Consider that \( I \) and \( J \) are two discrete random variables with marginal probability distributions \( p(i) \) and \( p(j) \), joint probability \( p(i,j) \), and \( p(i) \). The probability to observe \( I \) at time \( t+1 \) in state \( i \) conditional on the \( k \) previous observations is \( p(i_{t+1}|i_{t}, \ldots, i_{t-k+1}) \). The average number of bits needed to encode the observation in \( t+1 \), once the previous \( k \) values are known, is given in Eq. (16).

\[ h_i(k) = - \sum_{i} p(i_{t+1}|i_{t}, \ldots, i_{t-k+1}) \log p(i_{t+1}|i_{t}, \ldots, i_{t-k+1}) \] (16)

where \( \delta_{t}^{k} = (i_{t}, \ldots, i_{t-k+1}) \). analogously for process \( J \). Further, we calculate Shannon’s transfer entropy as given in Eq. (17).

\[ T_{I \rightarrow J}(k,l) = \sum_{i,j} p(i_{t+1}, j_{t+1}|i_{t}, j_{t}) \log \frac{p(i_{t+1}|i_{t}^{(k)})j_{t}^{(l)}}{p(i_{t+1}|i_{t}^{(k)})} \] (17)

where \( T_{I \rightarrow J} \) measures the information flow from \( J \) to \( I \). \( T_{I \rightarrow J} \), as a measure for the information flow from \( I \) to \( J \), can be derived analogously. The dominant direction of the information flow can be inferred by calculating the difference between \( T_{J \rightarrow I} \) and \( T_{I \rightarrow J} \).
We also calculate transfer entropy based on [56]; which depends on a weighting parameter $q$ and is calculated as:

$$H_{J}^{q}(I) = \frac{1}{1 - q} \log \sum_{j} p_{q}(j)$$

with $q > 0$

For $q \to 1$, Rényi’s entropy converges to Shannon’s entropy. For $0 < q < 1$ event that has a low probability receive more weight, while for $q > 1$ the weights favor outcomes $j$ with a higher initial probability. Thus, Rényi entropy emphasizes different areas of distribution, depending on the parameter $q$. With $q > 0$ to normalize the weighted distributions, Rényi transfer entropy is calculated as given in Eq. (18).

$$RT_{J \rightarrow I}(k, l) = \frac{1}{1 - q} \log \frac{\sum \phi_{q}(i^{(k)}|j^{(l)}) p_{q}(j^{(l)})}{\sum \phi_{q}(i^{(k)}|j^{(l)}) p_{q}(j^{(l)}) + 1}$$

(18)

5. Results

We start this section by analyzing the density plots of TOPSIS, COPRAS, and VIKOR scores that are given in Fig. 3. As expected, we observe that social welfare presents a multimodal distribution because the countries researched are in different levels of development. Next, when we analyze the success index of COVID-19 control, we see that, for the majority of the countries, the policy measures were not strong and were not effective to control total cases/population, new cases/population, total deaths/population, and new deaths/population, since the density is higher for the low score. However, we see that there is a more homogeneous utility function for the apps. Moreover, the plot shows that there are only a few apps with high performance, whereas the majority of the apps have a low utility function.

Next, we analyze the correlations for TOPSIS, COPRAS, and VIKOR scores. As shown in Fig. 4, although the correlations are weak due to repeated observations, app utility is greater when the success of COVID-19 control decreases. Seasonality and trends may also be the cause of these low correlations, which we will address further.

Since we have daily temporal series, we employed an autoregressive integrated moving average (ARIMA) to determine the autocorrelations and differentiation, and a moving average model to analyze the optimal quantities of lags from the plots of the autocorrelation function (ACF) and partial autocorrelation function (PACF) [70]. Additionally, we further analyze the transfer entropy among the three indexes. As Fig. 5 shows, the success of COVID-19 control increases over time, while app utility and social welfare decrease in 2021. Although social welfare is a stable index, there is a decrease in 2021 since there are fewer apps that had their reviews collected in 2021. This decrease occurred because the web scraper collected reviews from each app once; thus, in the final period of the collection, we had fewer reviews, especially from the USA and Canada, which are countries with a high welfare index.

As Fig. 6 shows, the ACF of the social welfare and the COVID-19
control success index indicates that there is no autocorrelation. The ACF of app utility shows a higher autocorrelation at lag 1, 4, and 28, which may indicate that customers are using the apps with a different frequency – some of them twice a week and others once a month. However, the autocorrelation is still low. Since we have inconclusive ACF, we can go to the transfer entropy with lag 1.

Fig. 7 shows the PACF plots. The greater autocorrelations can be seen in the plot of COVID-19 control success and social welfare, although this correlation decreases over time, that is, countries with high social welfare are more successful in controlling COVID-19, but as time goes by, countries with low social welfare may have increased their rate of control success.

Further, we measured the information flow between time series by using transfer entropy. The results show a negative information flow from perceived app utility to COVID-19 control success indexes, which may indicate that where we have higher food app utility, COVID-19 control success is lower.

We also analyzed the neural networks model with the best performance for each index, as shown in Table 2. We used 10-fold cross-validation. We trained the indexes with the best neural network and then evaluated the relative importance of the variables for app utility by applying Olden’s function [71].

As Fig. 8 shows, the day of the week plays an important role in app utility, which can be affected by special offers on weekdays. On the other hand, Asia has low relative importance since the Asia countries do not have as many reviews collected as the Western countries.

Table 2
Neural networks with the best performance for each index.

| Index                  | # layers | # neurons per layer | L1 Regularization | L2 Regularization | MAE    | MSE    |
|------------------------|----------|---------------------|-------------------|-------------------|--------|--------|
| COVID Control Success Index | 2        | 25                  | 0.000             | 0.000             | 0.070  | 0.014  |
| Social Welfare Index   | 4        | 50                  | 0.000             | 0.000             | 0.046  | 0.008  |
| App Utility Index      | 4        | 25                  | 0.000             | 0.000             | 0.145  | 0.033  |
Next, we analyze the impact of the social welfare and COVID-19 control success indexes on the app utility index, as shown in Table 3. We consider continent North America, the group of non-English languages, and the day of the week Monday as the baselines. H1a predicts that country social welfare negatively affects the perceived utility of food apps. Supporting H1a, the results show the significant and negative effect of the social welfare index on app perceived utility ($\beta = -0.017, p = 0.001$). Furthermore, H1b predicts that the success of COVID-19 control negatively affects the perceived utility of food apps. Supporting H1b, there is a significant and negative effect of successful control of COVID-19 on the perceived utility of apps ($\beta = -0.039, p < 0.001$). Altogether, these results show that the utility of the apps is greater for countries with a low COVID-19 control success index and welfare scores. Interestingly, app utility is highest on Mondays, which was our baseline. There is also a

![Fig. 8. Olden’s sensitivity analysis.](image)

Table 3

Impact on the app utility index.

|                      | Estimate | Std. Error | t value | Pr(>|t|) |
|----------------------|----------|------------|---------|----------|
| (Intercept)          | 0.367    | 0.004      | 100.258 | 0.000 ***|
| Social_Welfare_Index | -0.017   | 0.005      | -3.408  | 0.001 ** |
| COVID_Control_Success_Index | -0.039 | 0.003      | -13.217 | 0.000 ***|
| Trend                | 0.000    | 0.000      | -8.225  | 0.000 ***|
| Tuesday              | -0.007   | 0.002      | -4.301  | 0.000 ***|
| Wednesday            | -0.011   | 0.002      | -6.664  | 0.000 ***|
| Thursday             | -0.010   | 0.002      | -6.024  | 0.000 ***|
| Friday               | -0.006   | 0.002      | -3.805  | 0.000 ***|
| Saturday             | -0.009   | 0.002      | -5.224  | 0.000 ***|
| Sunday               | -0.010   | 0.002      | -6.258  | 0.000 ***|
| Language_healthy_type_English | 0.063 | 0.001      | 65.532  | 0.000 ***|
| Language_unhealthy_type_English | 0.100 | 0.001      | 104.259 | 0.000 ***|
| Continent_Asia       | 0.089    | 0.002      | 51.742  | 0.000 ***|
| Continent_Europe     | 0.107    | 0.001      | 102.546 | 0.000 ***|
| Continent_Latin_America | 0.114 | 0.002      | 62.267  | 0.000 ***|

Note(s): Signif. codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 "1.

Table 4

The impact on the percentage of unhealthy food.

|                      | Estimate | Std. Error | t value | Pr(>|t|) |
|----------------------|----------|------------|---------|----------|
| (Intercept)          | 0.502    | 0.004      | 140.419 | 0.000 ***|
| App_Utility_Index    | 0.008    | 0.002      | 3.874   | 0.000 ***|
| COVID_Control_Success_Index | 0.044 | 0.003      | 15.663  | 0.000 ***|
| Social_Welfare_Index | -0.016   | 0.005      | -3.216  | 0.001 ** |
| Trend                | 0.000    | 0.000      | 7.677   | 0.000 ***|
| Tuesday              | -0.002   | 0.002      | -1.419  | 0.156     |
| Wednesday            | -0.017   | 0.002      | -10.589 | 0.000 ***|
| Thursday             | -0.019   | 0.002      | -11.736 | 0.000 ***|
| Friday               | -0.015   | 0.002      | -9.193  | 0.000 ***|
| Saturday             | -0.009   | 0.002      | -5.320  | 0.000 ***|
| Sunday               | -0.008   | 0.002      | -4.874  | 0.000 ***|
| Language_healthy_type_English | -0.436 | 0.001      | -469.038| 0.000 ***|
| Language_unhealthy_type_English | 0.451 | 0.001      | 479.321 | 0.000 ***|
| Continent_Asia       | 0.006    | 0.002      | 3.560   | 0.000 ***|
| Continent_Europe     | -0.009   | 0.001      | -8.666  | 0.000 ***|
| Continent_Latin_America | 0.015 | 0.002      | 8.350   | 0.000 ***|

Note(s): Signif. codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 "1."
difference in the coefficients according to the day of the week, which reinforces the ACF result showing that there is a four-day lag. For instance, the negative coefficient is lower for Tuesday and Friday. App utility also varies according to the region. The highest perceived app utility was for Latin America ($\beta = 0.114$, $p < 0.001$), which makes sense since the continent has a low COVID-19 control success index and welfare scores.

Further, we analyze the impact of COVID-19 control success, country social welfare, and app utility on the proportion of ‘unhealthy food’ reviews (Table 4). H2a predicts that COVID-19 control success positively affects the proportion of unhealthy reviews. In line with H2a, the COVID-19 control success index has a significantly positive effect on the proportion of unhealthy reviews ($\beta = 0.044$, $p < 0.001$). Moreover, H2b predicts that the perceived utility of food apps positively affects the proportion of unhealthy reviews. Supporting H2b, there is a significantly positive effect of food app utility on the proportion of unhealthy reviews ($\beta = 0.008$, $p < 0.001$). Finally, H2c predicts that a country’s social welfare negatively affects the proportion of unhealthy reviews. Supporting H2c, the social welfare index has a significantly negative effect on the proportion of unhealthy reviews ($\beta = -0.016$, $p = 0.001$). Thus, the results show that food app utility and COVID-19 control success increase unhealthy food consumption online, and this effect is most pronounced in countries with a low social welfare score.

6. Discussion

The results show that countries with high social welfare and success in COVID-19 control have a lower perceived utility of food apps. These findings suggest that app companies should try to increase the perceived value for these countries, for example, by being more responsive in moments when demand increases – as in the case of lockdowns.

Further, the results show that success in COVID-19 control and perceived utility of food apps positively affect the proportion of unhealthy reviews, whereas social welfare has a negative impact. These findings suggest that since people stayed at home more in countries with high COVID-19 control, they consume more unhealthy food through apps. Also, individuals from countries with a low social welfare index gave more value to food apps and consumed more unhealthy food in the online environment during the COVID-19 pandemic.

This has important implications for public health policymakers, showing that the online food environment can be an important setting for interventions that aim at incentivizing healthy eating. Moreover, this paper contributes to the literature by answering recent calls to study the relationships we analyzed. For instance, future research can investigate whether anxiety mediated the effect of stay-home policies and the increase of unhealthy food consumption. Also, we only explored online consumption. Thus, future research can investigate whether the consumption of homemade healthy food compensated for the consumption of unhealthy food in the online environment.

7. Conclusions

This study takes an MCDM approach to evaluate the effect of country social welfare and success in COVID-19 control on perceived app utility; and the effect of country social welfare, success in COVID-19 control, and perceived app utility on the percentage of reviews about unhealthy food. Thus, this paper contributes to the MCDM literature by simultaneously exploring the “tradeoff” (using VIKOR), “utility functions” (utilizing COPRAS), and “distance to ideal solutions” (through TOPSIS) in understanding the negative effect of social welfare on the perceived utility of food apps and the interplay of these concepts on unhealthy food reviews.

The food environment is an important driver for healthy consumption, and it has a direct impact on non-communicable diseases, such as diabetes, obesity, and hypertension [73,74]. Determinants of the food environment have also been widely studied [75,76] and there is a strong and cohesive body of literature established in the field that posits there are multiple factors - psychosocial, external, organizational, and individual - that contribute to how each individual approaches food behaviors (e.g., [77]). We add to the food literature by showing the impact that online food environments can have on individual behavior towards food consumption.

This article also adds to a growing body of research about healthy food on apps and websites. These platforms have been an important driver for (un)healthy food consumption in the food environment literature (Downs et al., 2020), even though there are some studies concerning the perceived performance and functionalities of food apps (e.g., [26]), to the best of our knowledge, there is no study showing the relationship between app utility and unhealthy food consumption. Thus, we add to the healthy food literature by analyzing the content of the reviews instead of the features of the apps and by showing that the perceived utility of food apps positively affects the proportion of reviews about unhealthy food.

Scholars studying app reviews have focused attention on the impact of the reviews on consumers (e.g. [78]), and the impact of the consumers on reviews (e.g., [47]). In line with [79]; we show that the analyses of the reviews’ content can open up a new direction for online research by detecting differences in consumer behavior. Thus, our research contributes to the literature on app reviews by providing evidence that we can gain important insights by analyzing the comments about apps in their respective stores.

Author statement

Declarations of interest: none.

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Appendix A. Supplementary data

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