ARTICLE IN PRESS

Journal of Business Research xxx (xxxx) xxx

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Influencing subjective well-being for business and sustainable development using big data and predictive regression analysis

Vishanth Weerakkody *, Uthayasankar Sivarajah, Kamran Mahroof, Takao Maruyama, Shan Lu

School of Management, University of Bradford, United Kingdom

ARTICLE INFO

Keywords:
Big data
Regression
Well-being
UN SDG goals
Public sector

ABSTRACT

Business leaders and policymakers within service economies are placing greater emphasis on well-being, given the role of workers in such settings. Whilst people's well-being can lead to economic growth, it can also have the opposite effect if overlooked. Therefore, enhancing subjective well-being (SWB) is pertinent for all organisations for the sustainable development of an economy. While health conditions were previously deemed the most reliable predictors, the availability of data on people's personal lifestyles now offers a new dimension into well-being for organisations. Using open data available from the national Annual Population Survey in the UK, which measures SWB, this research uncovered that among several independent variables to predict varying levels of people's perceived well-being, long-term health conditions, one's marital status, and age played a key role in SWB. The proposed model provides the key indicators of measuring SWB for organisations using big data.

1. Introduction

It is widely accepted that the world's most valuable resource is no longer oil but data (Wiseman, 2018). The term 'Big Data' is characterized by large volumes of structured and unstructured data across diverse platforms, including multimedia content which is virtually impossible to process using traditional databases and software technology (Mayer-Schönberger & Cukier, 2013). Vast amounts of diverse types of data can now be captured at ease as a result of the exponential rise in computational power and storage abilities. The opportunities presented by this type of data can significantly impact both private and public sector organisations, as well as the wider society, including people's health and well-being. Therefore, in organisational and social contexts, there remains the pertinent question of how openly available big public data can be leveraged for knowledge discovery purposes beyond typical business decision making into key sustainable development priorities such as health and well-being (Westra, Wilbers, & Angeli, 2016).

According to the WHO (2017), chronic diseases are the main cause of death worldwide, however, this could be significantly lessened by addressing risk factors through early detection. The rise of big data has offered a new paradigm of data-driven studies, discovering hidden patterns in the data (Mayer-Schönberger & Cukier, 2013) and enabling earlier detection for significantly enhanced well-being.

There is a growing concern that well-being related issues are resulting in increased burden on public services such as health and social care. While studies have suggested a link between well-being and age – general health conditions, mental health (Slade, Johnston, Oakley Browne, Andrews, & Whiteford, 2009), family structure (Waldfogel, Craigie, & Brooks-Gunn, 2010), education and happiness (Michalos, 2017). Furthermore, there is a significant body of evidence linking inadequate management of well-being to negative and adverse impact on businesses and economies. For example, lower levels of workers' well-being is attributed to higher business costs to organisations (MacDonald, 2005), including higher medical care expenditure and employee compensation (Jee, O'Donnell, Suh, & Kim, 2001; Weaver et al., 1998), increased employee absences (Department for Work and Pensions, 2005; Jee et al., 2001; Weaver et al., 1998), lower levels of employee productivity (Druss, Schlesinger, & Allen, 2001; Goetzel, Ozminkowski, Sederer, & Mark, 2002), and early retirement (Pattani, Constantinovici, & Williams, 2001). These findings emphasise potential future business risks and liabilities as a result of well-being related issues. Thus, promoting well-being could assist in improving employee attitudes and increasing productivity, which in turn can enhance decision making, organisational effectiveness, and business success (Holmgren Caicedo, Mårtensson, & Roslender, 2010; Renee Baptiste, 2008). Therefore, given the increasing attention placed on well-being and its potential impact on business and economies, this research aims at exploring how survey-based analysis on subjective well-being (SWB) could be applied to big

* Corresponding author.
E-mail address: v.weerakkody@bradford.ac.uk (V. Weerakkody).

https://doi.org/10.1016/j.jbusres.2020.07.038
Received 30 August 2019; Received in revised form 25 July 2020; Accepted 27 July 2020
Available online 19 August 2020

data and offer meaningful insights into varying levels of people's perceived well-being. It would thus assist policy makers in taking informed decisions that could in turn improve the well-being of citizens and business performance, an approach which has had little academic focus to date.

SWB can be considered highly important within service dominated economies, given its role in progressing employee commitment and job satisfaction, thus also directly and indirectly impacting customer service and satisfaction (Barber, Hayday, & Bevan, 1999; Rhoades & Eisenberger, 2001). Therefore, a predominantly service-based economy such as the UK is largely reliant upon the "human capital" of employees, as opposed to tangible goods, therefore emphasising the need for proactive measures to monitor, manage and predict their SWB levels.

By appreciating both social and economic implications relating to SWB, this paper takes a proactive step in addressing the business-related challenges resulting from well-being issues.

In order to achieve this goal, the current study is proposed as the first phase of a two-phased research project; this paper being phase one is to develop a statistical model to predict SWB using publicly available national survey data. The current research proposes that the developed model be placed on online platforms to collect relevant real-time big data from the public. Upon building the model, phase-two of the research will focus on evaluating the merits of collecting, analysing and visualising data fed by the public to inform policy makers of citizen's SWB in real time. As far as the authors are concerned, there has been very few studies incorporating national survey data into big data analysis. We posit that our approach might possibly introduce a new avenue in the research area of open-big-data analysis and offer potentially significant contributions to the area of health and well-being in the context of sustainable development.

To realise the research aim, the paper is structured into eight sections. The next section reviews the literature on big data, United Nations Sustainable Development goals (UN SDGs) and well-being to uncover links between the three. Section three then proposes the research hypothesis to test these links. In Section four, the research method used for this study is discussed followed by the analysis of the findings in Section five. This is followed by a discussion in the next section, and Section seven discusses the empirical and practical implications of the study. The paper concluded in Section eight by summarising the main contributions and outlining the limitations of the study.

2. UN SDGs, big data and well-being: A review of literature

2.1. Exploring well-being as a concept

The literature on well-being is extensive, dating back over 40 years and has largely been addressed through various aspects of happiness, quality of life, and life satisfaction (Campbell, Converse, & Rodgers, 1976). While research on well-being can be explored from various perspectives, such as family-well-being (Dunifon, Ziol-Guest, & Kopko, 2014; Johnson & Markowitz, 2018; Thiyagarajan, Bagavandas, & Kosalram, 2019); elderly well-being (Hamid, Masood Ul Hassan, Haron, & Ibrahim, 2018; Othman & Fadzil, 2015; Ruengtam, 2017) and child well-being (Kitsaras, Goodwin, Allan, Kelly, & Pretty, 2018; Mazumder & Davis, 2013), majority of these studies are underpinned by the notion of Subjective Well-being (SWB).

Studies on well-being were previously centred on objective indicators in the form of absence of physical impairments, cognitive disabilities, and social restrictions (Rowe & Kahn, 1997). More recently it has extended to consider more subjective dimensions, such as positive psychological indicators which include complex constructs encompassing emotional stability, rational decision-making based on life knowledge, empathy, and compassion (Ardelt, 2016; Jeste & Harris, 2010). This trend towards SWB has been attributed to the fact that high levels of psychological well-being has the potential to counterbalance the adverse after-effects of chronic disease and disabilities (Bassi et al., 2014; Ryff, 2014).

According to Michalos (1980), SWB is defined as an individual's experience of affective reactions and cognitive judgments. An increasing amount of evidence suggests that SWB impacts health and other societal outcomes, further emphasised through the 'International Day of Happiness' initiated by the UN to express the importance of societal SWB as a key public policy objective (Diener & Tay, 2012; UN, 2013). Thus, there has been an underlying desire to capture individuals' perceptions of their states in various aspects of life (Kahneman & Krueger, 2006) with much emphasis being placed towards how people experience their lives in terms of both cognitive (satisfaction) and affective (happiness) reactions (Pan, Zinkhan, & Sheng, 2007). For example, Diener, Tay, and Oishi (2013) assess SWB through the use of life evaluation, positive feelings and negative feelings. Building on recent focus on individuals' perception to measure SWB, this paper will explore SWB in terms of individuals' perceptions including the sense of happiness, satisfaction and self-wroth.

2.2. Sustainable development goals and health and well-being

The UN SDG goals (SDG), introduced in 2015, are targets which signatory states such as the United Kingdom (UK) are required to meet individually and collectively. As such, the SDG3 Good health and Well-being concerns ensuring healthy lives and promoting well-being for all. Interestingly, whilst studies have placed significant emphasis on well-being in general, it seems their motivations have been to specifically explore well-being from a few particular contexts or groups of people such as the elderly, family, and children without focusing on other targets proposed in SDG3 goals. The SDG3 goal forwarded by the UN which concerns Health and Well-being are made up of a number of broader targets with the aim of measuring them through specific indicators. Accordingly, this paper aims to bridge this gap by offering well-being insights into SDG specific targets as endorsed by the UN.

2.3. Big data and Well-being opportunities

Big data presents unparalleled opportunities to accelerate scientific discovery and innovation in key areas that impact organisations and economies (Zhou, Chawla, Jin, & Williams, 2014). The utilisation of big data techniques is rampant within the private sector, with organisations successfully utilising them to offer personalised solutions (Anshari, Almunawar, Lim, & Al-Mudimigh, 2018), market segmentation, creative marketing (Erevelles, Fukawa, & Swayne, 2016), and predicting sales trends (Li, Ch'ng, Chong, & Bao, 2016). With organisations reaping much benefit from Big Data Analytics, there is a growing urgency to adopt similar techniques in order to gain real-time insights into individuals' well-being in order to target aid interventions to vulnerable groups (UN, 2013). While there is a timely discussion pertaining to the ethical use of big data analytics (Chen & Quan-Haase, 2018) with key concerns centred on privacy and security (Fang, Wen, Zheng, & Zhou, 2017; Jain, Gyanchandani, & Khare, 2019), it is argued that if the abundance of data, advanced technologies, and creative analytical approaches are responsibly enacted, this can lead to responsive, efficient, and evidence-based decision-making which may further improve the progress of the SDG goals, in particular SD3, in a comprehensive and reasonable manner (UN, 2018).

For instance, it is widely accepted that an active lifestyle can significantly improve health conditions, whereas failing to maintain an active lifestyle runs a high risk of developing a chronic disease, such as diabetes or cardio-vascular disease (CVD). Gachet Páez, de Buenaga Rodríguez, Puertas Sánz, Villalba, and Muñoz Gil (2018) discuss the potential of transforming how well-being may be monitored due to technological advancements such as, mobile communications, wearable computing, cloud and big data infrastructures, thus allowing individuals to track and monitor a person's health condition which may help prevent chronic disease. Therefore, the opportunities presented by capturing pervasive and real-time data may offer newer ways to understand an individual's well-being.

In addition to data derived from sensory technology, other forms of big data captured through social media posts could possibly explain well-being effectively. Studies have shown the increasing role of big data and social media analytics techniques in revealing how individuals feel and thus can also reflect important elements of well-being. For instance, many organisations are increasingly adopting big data techniques such as sentiment analysis, a technique which generally classifies with either positive, neutral or negative, across a range of polarity to reveal key insights into customers perceptions, feelings and emotional states. Sivarajah, Kamal, Irani, and Weerakkody (2017) reveal how organisations apply sentiment analysis in order to assess how consumers perceive their brands and actions from a sustainability viewpoint, therefore offering insights into more emotional and personal feelings of individuals. Similarly, there is a rising trend towards the use of digital footprints of social media users as a set of metrics to measure major determinants of well-being, as it offers a more detailed level of insights across time and space dimensions (Algan, Murtin, Beasley, Higa, & Senik, 2019; Huang et al., 2019; Lai, Hsieh, & Zhang, 2019). Chen, Chiang, and Storey (2012) explored the role of user-generated data and the digital traces resulting from social media sites such as Facebook and Twitter to measure, study, and even change SWB. Similar studies also have predicted individual level life satisfaction through big data measurement of Facebook status updates (Collins, Sun, Kosinski, Stillwell, & Markuzon, 2015), through measuring the type of Facebook pages liked (Kosinski, Stillwell, & Graepel, 2013), measuring life satisfaction words, emanating from Google Books (Hills, Proto, & Sgroi, 2017).

Accordingly, it is evident that the extant literature has largely attempted to predict survey responses to life satisfaction or questions relating to 'happiness' from an array of big data sources, particularly from individual's online digital footprints without being derived from SWB literature. The aim of this research, therefore, is to develop a big data SWB model which is underpinned by the appropriate normative literature with a specific focus on SDG targets as endorsed by the UN.

3. Conceptual model and hypothesis development

3.1. Influence of income on well-being

Although well-being and happiness have been explored from a plethora of factors, income is perhaps by far, the most researched (Deaton, 2008; Frijters, Geishecker, Haisken-DeNew, & Shields, 2006; Luhmann, Schimmack, & Eid, 2011; Stevenson & Wolfers, 2008; Tibesigwa, Visser, & Hodkinson, 2016), from a parental income and child well-being dyad (Blau, 1999; Brooks-Gunn & Duncan, 1997), personal income (Ravallion & Lokshin, 2002) as well as interdependent welfare functions (Bookwalter & Dalenberg, 2010; Frijters et al., 2006; Kingdon & Knight, 2007). Easterlin (1974) famously argued that increasing average income does not enhance average well-being, a claim widely referred to as the Easterlin Paradox. However, given data-rich environments and technological capabilities, collecting data have become easier in recent times, which has led to more rigorous testing of the Easterlin Paradox. As a result, a few studies have dismissed Easterlin Paradox by presenting evidence of positive relationship between well-being and income across several countries and over time (Deaton, 2008; Stevenson & Wolfers, 2008). There are several studies which explore many potential determinants of childhood well-being (Mazumder & Davis, 2013) with parental income considered as an important determinant of child well-being (Brooks-Gunn & Duncan, 1997).

The authors postulate that while high income improves evaluation of life (evaluative well-being), it fails to improve emotional well-being (Hedonic well-being).

H1. Those who **earn more** are more likely to report greater perceived well-being than those who earn less.

3.2. Influence of health conditions on well-being

There is little surprise that many studies have attempted to gain a better understanding of the role health plays in overall SWB. Health conditions are encompassing as per the WHO (1948), who define health as *'not merely the absence of disease or infirmity but a state of complete physical, mental and social well-being'*. Consistent with the WHO, Friedman and Kern (2014:722), refer to *Physical health* as one's ability and energy to complete a range of daily tasks; either diagnosed or not diagnosed with organic disease such as heart disease or cancer. Steptoe, Deaton, and Stone (2015) report a connection between physical health and SWB whereby poor health is seen to lead to reduced SWB, while high well-being can reduce physical health impairments.

The extent to which health impacts SWB is a relevant point of discussion, particularly given that studies have shown that over the last few decades, suicide rates in the US have not significantly lowered, despite many pertinent medical advances for diseases such as HIV/AIDS, cardiovascular disease and paediatric cancers (Kron et al., 2019). Thus, highlighting that high-income societies, which has seen much health-related advancements seemingly has limited positive impact on SWB, as reflected through the cause of death resulting from suicide. Therefore, there is a need for further exploration of health conditions from the context of SWB.

H2. Those with **prolonged ill health conditions** are more likely to report lesser perceived well-being compared with those without such health conditions.

3.3. Influence of co-habiting on well-being

While a significant segment of studies focus on the impact of cohabitation and marital status on child well-being (Brown, 2004; Goldberg & Carlson, 2014; Manning, 2015; Popenoe, 2009; Waldfogel et al., 2010), the relationship between well-being and cohabitation and/or marriage is widely reported in the extant literature. For instance, married individuals are consistently attributed to a greater SWB than unmarried individuals, whereas the latter are reported as having a greater SWB than divorced, separated, or widowed individuals (Glenn & Weaver, 1979; Gove, Style, & Hughes, 2016; Mastekaasa, 1994; Veenhoven, 1984). Furthermore, Soons, Liefbroer, Kalmijn, and Johnson (2009) found a significant SWB decrease was found after union dissolution, but subsequent adaptation or re-partnering led to a return in increased well-being. Their study also noted that well-being of never-married and never cohabiting young adults gradually diminished over time.

Willoughby and Belt (2016) report low well-being between cohabiting couples when lower importance was placed on marriage. Their study offers further evidence that cohabiting couples are not all the same and marital orientations and engagement status are important indicators of relationship well-being.

Thus, there is a need to explore this further.

H3. Those who **live with someone else** (married or cohabiting) are more likely to report greater perceived well-being than those who live on their own.

3.4. Influence of religious beliefs on well-being

Religion is considered as a powerful coping mechanism (Pargament & Park, 1997), therefore the endorsement of religion or spirituality as being consistently linked with higher levels of well-being in unsurprising (Koenig, 2012); Koenig, King, & Carson, 2012). Several studies have explored why people turn towards religion and spirituality and found seeking refuge from negative psychological experiences and emotions as a key trigger (Saroglou, Buxant, & Tilquin, 2008). For instance,

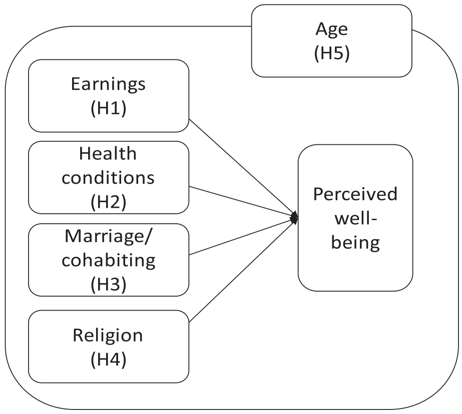

Fig. 1. Conceptual model.

situations such as socioeconomic sufferings (Wimberley, 1984), death of loved ones (Michael, Crowther, Schmid, & Allen, 2003), illness, and negative life experiences (Spilka, Hood, Hunsberger, & Gorsuch, 2003) were all seen as catalysts which lead to the uptake of greater religious and spiritual involvement.

Therefore, studies suggest a positive association between several indicators of religion and spirituality and positive outcomes which typically align with SWB, such as satisfaction of life (Ellison & Fan, 2008), optimism and sense of self-worth (Whittington & Scher, 2010), and hope (Ai, Park, Huang, Rodgers, & Tice, 2007). This research therefore expects to gain a closer understanding of how and why religion and spirituality are related to well-being and to what extent this can be used as a means to predict future well-being.

H4. Those **with religious beliefs** are more likely to report greater perceived well-being than those without one.

3.5. *Influence of age on well-being*

One of the key challenges in current times is to enable people to age well (Nazarko, 2015). It is widely accepted that SWB as an area of research has produced many intriguing findings, particularly the relationship between SWB and age (Horley & Lavery, 1995). For instance, previous studies have revealed contradictory results, with some studies indicating no relationship between age and SWB (Costa et al., 1987; Diener, 1984), whereas Wilson (1967) report younger people are happier than the older. Veenhoven (1984) probe this further by highlighting that with age, hedonic levels decrease whilst contentment increases. Given the conflicting views surrounding this, there is a need for further exploration of the age well-being dyad.

H5. These hypotheses are moderated by **age** where younger and older people are more likely to report higher perceived well-being.

While extant studies have explored the aforementioned variables individually or in conjunction with others as a means to see its relationship with SWB, studies to date have not incorporated Income, Health Conditions, Marriage/Cohabitation, Religion and Age together to explore perceived SWB. As a result, this study proposes the following novel conceptual model (Fig. 1) highlighting the factors that affect well-being.

In line with the recommendations of Monroe, Pan, Roberts, Sen, and Sinclair (2015), this research combines theory and data analysis, drawing from the SWB literature, thus presenting many benefits. It can be argued that firstly it is appropriately grounded in the existing well-being literature, is transparent, can be considered as testable and is adaptable, presenting the opportunity for it to be potentially applied to predict well-being on a continuous and recurrent basis.

4. Research methodology

4.1. *Data*

Data for our research were obtained from the Annual Population Survey (APS) in the United Kingdom, which is publicly available. The APS is one of the largest UK national surveys funded by the government, and each APS dataset contains 12 months of data, including approximately 300,000 individuals living in the UK. The large majority of the APS data are derived from another UK national survey, the Labour Force Survey (LFS), whose data are collected based on the random sample of UK postcodes. This core dataset is reinforced by additional samples from boost and enhancement surveys in Great Britain. This effectively renders the APS the largest coverage of any household survey in the UK (ONS, 2011). The APS contains about 500 variables and a wide range of survey topics including demographic variables (e.g. age, sex, ethnicity, educational qualification, religion), employment-related variables (e.g. employment status, income, working hours, occupation, industry), and health conditions. To achieve our research aim of exploring the role of big data in assisting effective decision making in the realm of well-being, the survey data were most pertinent because of its widest coverage of the UK population and its relevant topics available to our research.

For the specific purpose of our research, two types of datasets were employed; the most recent three-year (from 2015 to 2017) pooled dataset at the time of writing was obtained for building a regression model to initially identify relationships between the dependent, independent, controlling, and moderating variables. The three-year pooled dataset contained 530,300 respondents. A weighting variable was used to report findings based on the population. Secondly, six individual APS datasets (from 2012 to 2017) were used for forecasting purposes. The reason that we were not able to include data from earlier years was because the dependent variable, perceived well-being, was introduced only in the April-June quarter of the LFS in 2011 in the UK, so the first APS dataset that contains well-being is from 2012.

4.2. *Measures*

4.2.1. *Dependent variable*

The APS includes four well-being variables of: satisfaction ("Overall, how satisfied are you with your life nowadays?"), worth ("Overall, to what extent do you feel that the things you do in your life are worthwhile?"), happiness ("How happy did you feel yesterday?"), and anxiety ("How anxious did you feel yesterday?"). Respondents aged 16 and over at the time of the survey were asked to report their SWB statuses based on a Likert scale ranging from 0 (Not at all satisfied/worthwhile/happy/anxious) to 10 (Completely satisfied/worthwhile/happy/anxious). To facilitate statistical analyses, 0 was converted to 1, 1 was converted to 2, 2 to 3, and so on, and the revised scale ranges from 1 to 11 for all variables except for 'anxiety'. For 'anxiety', all values were reversed; 0 was converted to 11, 1 to 10, and so forth. The internal consistency was measured using Cronbach's test, which suggested the anxiety variable would lower the internal consistency with Cronbach's alpha from 0.80 to 0.75. Based on this, it was decided to drop the anxiety variable and keep the first three variables to create an overall 'well-being' variable for the analysis. The derived dependent variable on well-being was the arithmetic mean of values from the three well-being variables.

4.2.2. *Independent, controlling, moderating variables*

The APS covers a wide range of topics, and the following independent variables were selected for our research: marital/co-habiting status (Married/cohabiting/civil partner or Non married), long-term illness lasting 12 months or more (Y/N), religious denomination (Y/N), accommodation type (Owned outright/Being bought with mortgage or loan/Part rent, part mortgage/Rented/Rent free, etc.), and income (combined weekly income from the main and second job, if a respondent had a second job). Respondents' age was selected as a moderating

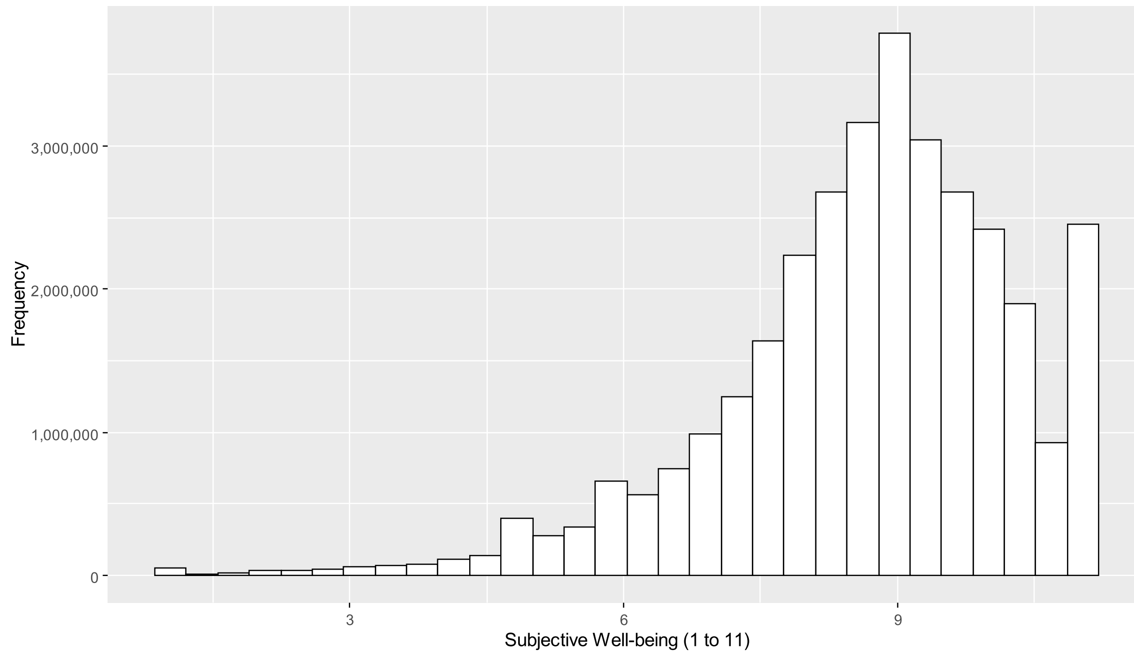

Fig. 2. Distribution of SWB (n = 32,805,995).

variable. Respondents' sex and ethnicity were also used as controlling variables in order to control for the effects of the two basic demographic characteristics whilst focusing on the effects of independent variables for hypothesis testing.

4.2.3. Regression model

The data type of the dependent variable was ordinal with 11 levels of perceived well-being. Initially, the binary logistic regression model was considered to be used for the analysis, however, the distribution of the data was positively skewed with more than half of the sample was found in the three highest levels (9 to 11). This high concentration of well-being scores at the higher end made it difficult to draw meaningful boundary between "lower" and "higher" well-being with comparable numbers of respondents observed in the two groups. Given this, it was decided to create five well-being categories; "Below 7", "At least 7 below 8", "At least 8 below 9", "At least 9 below 10", and "10 and 11" with comparable observations in each well-being category (11.1%, 11.8%, 24.6%, 29.0%, and 23.5% of the sample of 32,805,995 individuals respectively). "Below 7" was set as the reference group to be compared against the remaining four well-being groups in turn, and multinomial logistic regression analysis was employed as the appropriate method to make these comparisons and identify statistically significant predictors

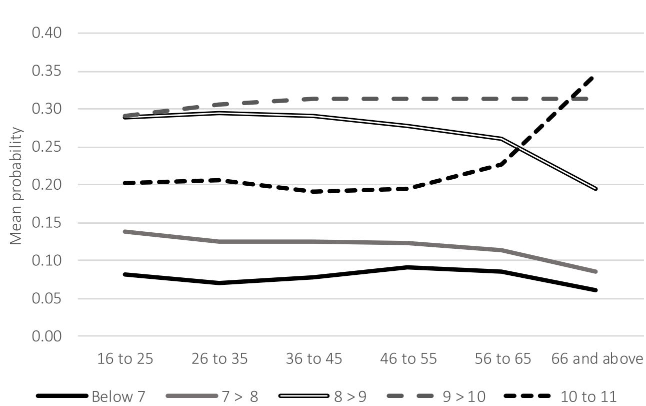

Fig. 3. Mean probability of reporting differing levels of well-being by age group.

for the dependent variable of SWB.

4.2.4. Predictive regression analysis

The purpose of the predictive regression analysis is to provide an insight of useful tools for predicting the well-being state of an individual based on a sample/population of individual data collected from surveys. This is of particular interest to organisations such as local governments, councils and charities where the well-being state of people is important for decision making with regard to the distribution of public resources. The question of interest in the predictive regression analysis is whether or not the well-being state of an individual can be predicted from the individual's personal conditions based on a model constructed from a large pool of data containing people's personal conditions and well-being states.

4.2.4.1. Prediction with logistic regression. The logistic regression is a statistical method that models the probability of possible outcomes of the response variable. It assumes that the log-probability is a linear combination of independent variables (predictors). logistic regression is adequate for prediction when the response variable is an unordered, categorically distributed variable (Wooldridge, 2010). Unordered variable is a variable which falls into any of the possible outcomes that cannot be ordered in a meaningful way. Examples of unordered response variables include health plans, choices of commuting to work, and occupational choices (Wooldridge, 2010). Well-being state is such an unordered variable.

Logistic regression is widely used for prediction purposes in clinical medicine, engineering, social sciences and economics. Hossain, Wright, and Petersen (2002) use multinomial logit model to forecast the arrival time at hospitals after onset of symptoms, whereas Truett, Cornfield, and Kannel (1967) employ the same model to predict the risk of developing heart diseases based on the observed vital signs of patients. Palei and Das (2009) employ logistic regression for the prediction of roof fall risks in pillar workings in coal mines. Murata, Fujii, and Naitoh (2015) test the effectiveness of the multinomial logistic regression model in predicting driver's drowsiness. Berry and Linoff (1997) use the multinomial logistic regression as a tool in marketing to predict customer's tendency to purchase a product. Stratton, O'Toole, and Wetzel (2008) discriminate the behaviour of college stopout and dropout by using the logistic regression.

In this paper we view the prediction of the well-being states as an ordinal classification problem with ordering information, with the probability of being in each well-being state to be precited. In the case of two well-being states, the naïve approach of directly applying the binary logistic model for prediction is straightforward and simple to implement. The problem lies in the case of more than two well-being states to be predicted. Frank and Hall (2001) proposes a simple learner's tree approach for the ordinal classification problem. The approach performs better than the naïve multinomial logic model in predicting the probability and for classification tasks and can be easily incorporated with machine learning algorithms. Details of the approach refer to Frank and Hall (2001; Fig. 2).

We recognize that there are some other popular approaches that complement our approach in terms of prediction analytics. First, the Internet of Medical Things is an ecosystem of connected wearable medical devices which generate, collect, analyse and transmit healthcare data into the cloud, and the integrated big data and predictive analytics are capable of carrying out classification of information, thoroughly predicting and diagnosing patients' likely conditions, which eventually prevents and handles chronic diseases. The Internet of Medical Things provides efficient, adequate, instantaneous and inexpensive remote monitoring, and is decisive for patients (Byerly, Vagner, Grecu, Grecu, & Lazaroiu, 2019; Krech, 2019; Watts-Schacter & Kral, 2019). Second, Fuzzy logic is a process that uses many-valued logic where true values of variables range between zero (completely false) and one (completely true). It mimics the human decision-making process and is capable of processing linguistic information. Capuano, Chiclana, Herrera-Viedma, Fujita, and Loia (2019) proposes a group recommendation system based on the fuzzy logic by aggregating the preferences of group members without taking individual characteristics into decision-making. A similar system for group decision making but guided by social influence based on the fuzzy logic theory is also proposed by Capuano, Chiclana, Fujita, Herrera-Viedma, and Loia (2018). Fujita, Gaeta, Loia, and Orciuoli (2019) presents an interactive method built on the combination of probability, fuzzy and rough set theories that is capable of processing intelligence information with the application to counterterrorism.

For the purpose of illustration of the prediction method, a binary logistic regression is employed; our data sample consists of personal information as well as the well-being state of 358,714 individuals. The prediction is performed as follows. Firstly, the first half of the data is used as the training data to construct and estimate the binary logistic regression model. Secondly, the other half of the data is used as the prediction sample, by inputting personal conditioning variables into the estimated binary logistic regression model, predicted probabilities of high/low well-being states are obtained. Thirdly, by using a cut off probability (0.5), the predicted well-being state is determined. Lastly, the predicted well-being state is compared to the observed well-being state by using several performance measures.

4.2.4.2. Performance measures. Several performance measures are employed to quantify the prediction performance of the logistic regression, including the classification table and predictive efficiency indexes.

The classification table shows the number of correctly predicted well-being states by the logistic regression model compared to the total number of observed, and the number of falsely predicted well-being states by the logistic regression model compared to the total number of observed.

Based on the classification tables, three predictive efficiency indexes, λp, τp and φp, can be constructed (Menard, 1995; Ohlin & Duncan, 1949):

Table 1
Descriptive statistics – Subjective well-being* (based on the Likert scale 1–11).

	n	Mean	SE
Well-being	**3,28,05,995**	**8.70**	**0.004**
Satisfaction	3,29,57,625	8.68	0.004
Worth	3,28,54,904	8.89	0.004
Happiness	3,29,44,179	8.52	0.005
Anxiety	3,29,16,625	8.12	0.007

* Respondents aged 16 and above at the time of the survey.

$$\lambda_p = 1 - \left(n - \sum f_{ii}\right) \Big/ (n - n_{\text{mode}}),$$
$$\tau_p = 1 - \left(n - \sum f_{ii}\right) \Big/ \left[\sum f_i(n - f_i)/n\right],$$
$$\phi_p = 1 - \left(n - \sum f_{ii}\right) \Big/ \left[n - \sum E(f_{ii})\right]$$

where $E(f_{ii}) = \left[\sum_i f_{ij}\right]\left[\sum_j f_{ij}\right] \Big/ n$, n is the sample size, n_mode is the observed number of individual cases in the modal category of the response variable (well-being state), f_ij is the total number of having observed well-being state i but predicted as having well-being state j, f_ii is the number of correct prediction for well-being state i. All three indexes are interpreted as proportional reduction in error. A negative value of the predictive efficiency index indicates the model does worse than expected; a value of zero indicates no relationship between the conditioning variables and the response variable (well-being state); and a value of unity indicates the perfect prediction (well-being state of all individuals in the prediction sample are correctly predicted).

The statistical significance is implied by the normal approximation of a binomial *d*

$$d = \left(\frac{P_e - p_e}{\sqrt{P_e(1 - P_e)/n}}\right)$$

where Pe = (error without model)/n, and pe = (error with model)/n; error without model and error with model can be calculated from the predictive efficiency indexes, with different specifications for different predictive efficiency indexes [for details refer to Menard (1995)].

When the question of interest is whether or not the model increases the accuracy of prediction of the response variable (well-being state), a one-tailed test of the statistical significance of the predictive efficiency indexes is adequate. The null hypothesis of the one-tailed test is that proportion of errors with the model is not smaller than the proportion of errors without the model; and the alternative hypothesis is that proportion of errors with the model is smaller than the proportion of errors without the model (Menard, 1995). Significant predictive efficiency indexes indicate that the conditioning variables are relevant to the classification of the well-being state, and allow one to classify the well-being state with some degree of accuracy.

5. Findings and analysis

5.1. Descriptive statistics and bivariate statistical analyses

The large majority reported greater SWB with the means ranging from 8.12 for anxiety to 8.89 for self-worth (Table 1). The mean of the overall well-being score (excluding the item on anxiety) were at 8.70 as reflected on the negatively skewed distribution of the well-being statistic (Fig. 2).

Some strong statistical associations were found between SWB and respondents' demographic variables (Table 2) and summarised as follow:

- Those who were married/cohabited were more likely to enjoy greater SWB ($\bar{x} = 8.94$) compared with those who lived on their own ($\bar{x} = 8.31$).

Table 2
Bivariate statistical results: Association between well-being and relevant variables (Chi-square test).

	Group	n	mean	se	Test statistic	df	sig
Marital status					19947.0	4	<0.001
	Married/cohabiting/civil partner	2,00,23,962	8.94	0.00			
	Non-married	1,27,82,033	8.31	0.01			
Long-term illness					16144.0	4	<0.001
	With long-term health issues	1,28,41,482	8.39	0.01			
	Without long-term health issues	1,85,16,377	8.91	0.00			
Age					9643.1	20	<0.001
	16–25	27,15,918	8.65	0.01			
	26–35	53,05,603	8.70	0.01			
	36–45	52,94,368	8.61	0.01			
	46–55	61,15,301	8.49	0.01			
	56–65	53,59,786	8.68	0.01			
	66 and above	80,15,019	8.93	0.01			
Income					5685.4	12	<0.001
	£1–£249 per wk	33,67,601	8.75	0.01			
	£250–£403 per wk	32,38,882	8.69	0.01			
	£404–£634 per wk	36,24,089	8.75	0.01			
	£635 or higher per wk	38,66,609	8.82	0.01			
Sex					1225.0	4	<0.001
	Male	1,49,04,786	8.65	0.01			
	Female	1,79,01,209	8.74	0.00			
Religion					3602.1	4	<0.001
	No religion	1,07,29,882	8.54	0.01			
	With religion	2,12,24,025	8.77	0.00			
Accommodation type					13121.0	4	<0.001
	Rented/part-mortgage	1,09,14,318	8.35	0.01			
	Owned/rent-free/squatted	2,18,74,835	8.87	0.00			
Ethnicity					1011.4	16	<0.001
	White	2,95,26,450	8.71	0.00			
	South Asian	12,17,991	8.73	0.02			
	Black	8,46,291	8.40	0.03			
	Other Asian/Chinese	4,65,220	8.67	0.03			
	Mixed/Other	7,29,030	8.54	0.03			

- Those with long-term health issues were more likely to report lower SWB ($\bar{x} = 8.39$) than those without ($\bar{x} = 8.91$).
- In terms of respondents' age, older (66 and above) people appeared to experience greater SWB ($\bar{x} = 8.93$ for '66 and above', compared with any other age groups).
- High income earners were generally more likely to report greater well-being with the mean well-being among the lowest income group at 8.75 against that of the highest income group at 8.82.
- Females were more likely to report higher well-being than males ($\bar{x} = 8.74$ vs. 8.65).
- Those who named any religion in response to a question, "What is your religion?", were more likely to report greater SWB ($\bar{x} = 8.77$ vs. 8.54)
- Those who owned accommodations/rent-free/squatted were more likely to report higher well-being than those who rented/part-mortgaged ($\bar{x} = 8.87$ vs. 8.35).
- Black and mixed/other ethnic people were likely to report lower ($\bar{x} = 8.40$ and 8.54, respectively) SWB than people from other ethnic background.

5.2. Regression analysis

A series of multinomial logistic regression models were created using only controlling variables (Model 1 - sex and ethnicity only), predictors and controlling variables (Model 2), and predictors, controlling variables and age as a moderating variable (Model 3). In each of these models, the following four comparisons were made:

- Comparison 1: "Below 7" vs. "At least 7 below 8"
- Comparison 2: "Below 7" vs. "At least 8 below 9"
- Comparison 3: "Below 7" vs. "At least 9 below 10"
- Comparison 4: "Below 7" vs. "10 and 11"

These comparisons are presented respectively in Tables 5–8 in Appendix A.

Model 1 included only the two controlling variables of sex and ethnicity. The two controlling variables were included in order to control for the effect of the two variables, and their effects are not discussed in the analysis. In Model 2 (controlling variables and predictors only), across these four comparisons, the following patterns were observed which were in line with the chi-square test results presented in the above section $b = -0.29, p < .001$ in Comparison 1 to $b = -1.07, p < .001$, suggesting that those who were not married/cohabiting were more likely to report lower SWB compared with those who were married/cohabiting, and that the magnitude of the probability of reporting greater well-being was highest in Comparison 4 where the bottom and top well-being categories were compared. This supports H3. Likewise, the coefficient of long-term illness continued to grow from $b = -0.38$, $p < .001$in Comparison 1 to $b = -0.92, p < .001$ in Comparison 4, indicating that those with long-term illness were most likely to report the lowest well-being category. This finding supports H2. Similarly, the coefficient for religious denomination multiplied from $b = -0.01, p < .001$ to $b = 0.33, p < .001$, suggesting that those with religions were more likely to report greater well-being; this supports H4. In terms of income, although those people with higher income were generally more likely to report greater well-being in Comparison 1, 2, and 3 (e.g. $b = 0.58, p < .001$ for "£635 or higher per week" in Comparison 3), this pattern appeared to be lessened in Comparison 4 (e.g. $b = 0.19, p < .001$ for "£635 or higher per week"). So, this partially supports H1. The coefficient for accommodation type was $b = 0.19, p < .001$ in Comparison 1 and $b = 0.30, p < .001$ in Comparison 4.

Turning to Model 3, which included all variables in Model 2, plus age as the moderating variable, associations between the dependent and independent variables were similar to those found in Model 2. With regard to "married/cohabiting", the coefficient was $b = -0.32, p < .001$ in Comparison 1 and rose to $b = -1.14, p < .001$ in Comparison 4. For

Table 3
Model contributions by predictor.

Predictors	Model 1 *Chisq*	*df*	*p*	Model 2 *Chisq*	*df*	*p*	Model 3 *Chisq*	*df*	*p*
Married/cohabiting				2,80,103.0	4	<0.001***	3,00,519.0	4	<0.001***
Health conditions/illnesses lasting 12 months or more				1,79,249.0	4	<0.001***	1,68,833.0	4	<0.001***
Age							93,967.0	20	<0.001***
Weekly gross income (£)				86,946.0	12	<0.001***	84,344.0	12	<0.001***
Sex	76,905.0	4	<0.001***	34,544.0	4	<0.001***	58,660.0	4	<0.001***
Religious denomination				39,938.0	4	<0.001***	35,642.0	4	<0.001***
Accommodation type				29,014.0	4	<0.001***	40,082.0	4	<0.001***
Ethnicity	59,390.0	16	<0.001***	27,516.0	16	<0.001***	27,581.0	16	<0.001***
R^2 (McFadden)	0.002			0.600			0.601		
Change in R^2	n/a			0.598			0.001		
Residual deviance (-2LL)	1,08,85,423.7			44,75,223.4			43,81,256.3		
Change in residual deviance (-2LL)	n/a			64,10,200.4			93,967.0		

"Long-term illness", the coefficients strengthened from $b = -0.33, p < .001$ in Comparison 1 to $b = -0.90, p < .001$ in Comparison 4. Likewise, religious denomination had coefficients $b = 0.05, p < .001$ in Comparison 1 and $b = 0.37, p < .001$ in Comparison 4. Thus, these results in Model 3 support H2 to H4. These three findings were also endorsed by odds ratios presented in Figs. 4–7 (Comparison 1 to 4, respectively) in Appendix A. In terms of income, again similar patterns were observed where those who earned higher income were generally more likely to report greater well-being in Comparison 1, 2, and 3. However, this variable seemed to have a lower impact in Comparison 4; for example, the coefficient for "£635 or higher per week" in Comparison 3 was $b = 0.69, p < .001$, but it decreased to $b = 0.36, p < .001$ in Comparison 4. This was also noted in odds ratios for the top two income groups declining from Comparison 3 to Comparison 4 (see Figs. 6 and 7 in Appendix A). These findings suggest that our study finding partially supports H1, as the coefficient of income lowered among the highest well-being group.

Age was added to Model 3 in order to ascertain if our study results support H5; younger and older people were more likely to report higher perceived well-being. Mean probabilities of reporting differing levels of SWB by age group were calculated and presented in Fig. 3. Regardless of age, people were less likely (below 15%) to report lower SWB as presented in the lines for "Below 7" and "At least 7 below 8". The most likely level of SWB was "At least 9 below 10" (30% or higher). These were also clear in the descriptive statistics presented in the above section. What is worth noting is the declining trend of mean probabilities from age 16 to 25 to 66 and above for the bottom three well-being categories (i.e. "Below 7", "At least 7 below 8", and "At least 8 below 9"), suggesting that younger people were more likely to report these levels of SWB than their older counterparts. In contrast, among the top well-being category ("10 and 11"), a general upward trend from the younger to the older age group was observed. In particular, people in the top age group, 66 and above, were most likely to report the highest level of SWB than other younger groups. This supports partially H5 which tested if younger and older people were more likely to report higher perceived well-being than people in the middle-age groups; our results suggests that older people, particularly 66 and above, were more likely to report greater well-being than any other age groups. This was also clear in Comparison 3 (Fig. 6) and 4 (Fig. 7) in Appendix A where odds ratios and the lower confidence interval boundaries for age 66 and above exceeded one whilst the equivalent statistics for other age groups were below one.

Model 3 which are based on all the independent, controlling, and moderating variables offers the statistics of the goodness of it at 0.601, suggesting that 60 per cent of the variability could be explained by the model. The level of contribution of each predictor and moderating variable to the model (Table 3) was measured by calculating chi-square statistics. The results showed that people's marital/co-habiting status was found to be the most powerful predictor $(x(4) = 300519.0$, $p < .001)$, followed by long-term health condition $(x(4) = 168,833.0$, $p < .001)$, age $(x(4) = 93,967.0, p < .001)$, and income $(x(4) = 84,344.0, p < .001)$. Religious denomination or accommodation type were not as strong as those predictors. The results might suggest that these top predictors could be key characteristics that policy makers should focus on when predicting people's SWB.

Table 4
Out-of-sample prediction of binary logistic regression model.

Dependent Variable Wellbeing	Prediction/Classification Tables	Predicted Low (<9)	Predicted High (≥9)	% Correct	Predictive Efficiency	Binomial Statistics
Observed (n = 179357)	Low (<9)	51,565	35,155	59.46	$\lambda_p =$ 0.1040***	$d_{\lambda_p} =$ 42.6059
	High (≥9)	42,548	50,089	54.07	$\tau_p =$ 0.1326***	$d_{\tau_p} =$ 56.0933
			Overall	56.68	$\phi_p =$ 0.1349***	$d_{\phi_p} =$ 57.2451

***, **, * denote significance at 1%, 5% and 10% significance level.

5.3. Prediction performance

Table 4 reports the out-of-sample prediction performance of the binary logistic regression. It shows that the model is able to correctly predict the well-being states of 51,565 out of 86,720 (59.46%) individuals who have an observed well-being state of "low", and correctly predict the well-being states of 42,548 out of 92,637 (54.07%) individuals who have an observed well-being state of "high". The overall percentage of correct predictions is 56.68%. All three predictive efficiency indexes are positive and statistically significant at 1% significance level, indicating that the conditioning variables are relevant to the prediction of the well-being state, and increase the accuracy of prediction of the well-being state. The results reinforce our findings in the previous sections.

Our results have important implications for organisations in the public sector such as city councils and charities where the well-being state is an important factor in decision making involving the distribution of public resources. Our results indicate that these organisations can use exiting pool of data of information about people's well-being states and their personal conditions such as the eight conditioning variables examined in this paper to construct a model (logistic regression is a simple example of the model choice) of the well-being state. In practice, this can assist organisations and governments to make effective decisions when prioritising the service needs of customers/people by forecasting their well-being state where needed.

6. Findings and discussions

The research has produced some interesting insights into SWB, with many of the findings also resonating with previous studies. Findings from this study indicate that individuals who were not married/cohabiting were more likely to report lower SWB compared with those who were married/co-habiting. A plethora of studies have previously established that married couples are attributed to having greater SWB than unmarried individuals (Mastekaasa, 1994; Veenhoven, 1984). This has been attributed to many factors, including social isolation, whereby individuals who are not married are less happy due to the likeliness of them living alone in the absence of continued companionship (Shields & Wooden, 2003). This is supported by earlier studies which reveal married individuals are not only happier, but also more emotionally stable than their unmarried individuals (Diener, 1984; Diener, Suh, Lucus, & Smith, 1999).

However, it must be highlighted that while studies have explored the impact of marriage and SWB, studies have largely overlooked the role of cohabitating couples and SWB, which has also been considered in conjunction with marriage in this research.

Similarly, and in line with previous research, findings from this study also highlight that individuals with long-term illness were most likely to report the lowest well-being category. Steptoe et al. (2015) discuss an association between physical health and subjective well-being in which poor health is ascribed to reducing SWB. This too is supported by the findings of this research, thus emphasising the negative impact of long-term illness on SWB. Therefore, from the insights provided through the predictive model of this research, it can be concluded that if governments and employers actively pursue policies and agendas aimed at improving the health status of individuals and employees, this can in turn positively impact and improve the overall citizens' SWB.

Another key point of discussion in this research was exploring the extent to which age would impact SWB. Accordingly, the findings from this research revealed that people in the top age group, 66 and above, were most likely to report the highest level of SWB than other younger groups. Previous studies have given rise to conflicting views surrounding this, with some studies reporting no relationship between both, whereas others have provided evidence suggesting otherwise. Although research into SWB and older age is at an early stage, evidences indicate positive hedonic states, life evaluation, and eudemonic well-being are pertinent to health and quality of life as people age (Steptoe et al., 2015). Thus, it must be highlighted that the overall well-being of elderly people is a significant objective for both economic and health policy, which through the application of the proposed model from this research can be explored further.

Our research also finds that people with higher income were generally more likely to report greater well-being. For example, Steptoe et al. (2015) explore income and well-being from a contextual perspective, and find that in high-income English-speaking countries, life evaluation dips in middle age, and rises in old age. Highlighting this further, Diener and Biswas-Diener (2002) states that the increase of income may enhance SWB, given it takes individuals out of poverty and leads to habitation in a developed nation. However, individuals who are considered well-off and have increased material desires with the rise in their incomes, experience limited SWB over the long-term. This is in line with the findings made in our study where amongst those who from the highest SWB group, income made a limited contribution to the model. Thus, based on the results from this research and the exploration of related studies, it can be argued that income only has the potential to enhance SWB once it assists individuals in fulfilling basic needs.

This research offers further insights into SWB which is in congruent with existing studies, such as the findings that individuals who held religious beliefs were more likely to report greater well-being. Resonating with this, Deaton and Stone (2013) produce similar findings which suggests that religion acts as a coping mechanism for individuals, thus allowing them to overcome anxiety and personal troubles. It has previously been reported that religious people report greater SWB (see Hackney & Sanders, 2003; Koenig & Larson, 2001), which can be attributed to a number of factors such as religious people tend to have higher morale (Koenig, Kvale, & Ferrel, 1998), encounter fewer psychosocial pathologies such as domestic abuse (Waite & Lehrer, 2003), religious affiliations are linked to lesser depressive symptoms, a smaller amount of anxiety and better quality of life indicators (Huang & Chen, 2012) and also have higher levels of late-life well-being (McFadden, 1995). Accordingly, this research further supports this through empirical insights. However, previous studies have also indicated how SWB may vary across developing and developed countries (Ngamaba, Panagioti, & Armitage, 2017). Supporting this further from a context perspective, it has also been previously highlighted that religion impacts SWB more positively for poorer countries than developed countries, largely due to people who have lower levels of agency and lesser capabilities (Graham & Crown, 2014). Resonating with this and underpinned by the Gallup World Poll (GWP), Diener, Tay, and Myers (2011) too find that individuals from developing countries are much more likely to be religious than individuals belonging to nations and states who have more favourable conditions, thus placing emphasis for the need to explore religion and SWB across contextual lenses.

In summation, the model has helped identify that people's marital/co-habiting status was proven to be the most powerful predictor, which is followed by long-term health conditions and income. The other dimensions were not as strong as the aforementioned predictors.

7. Empirical and practical implications

Our models are based on publicly available national survey data which are not classed 'big data' in terms of volume, variety, or velocity. However, our regression model offered the statistic of the goodness of fit at 0.601 which is higher than that of other large survey studies which look into SWB; goodness of fit statistics reported in these studies are typically around or below 0.40 (e.g. Evans, Kelley, Kelley, & Kelley, 2019; Green & Elliott, 2010; Kapteyn, Lee, Tassot, Vonkova, & Zamarro, 2015; Piper, 2015). Though, we appreciate that despite the above, goodness in-sample performance does not implicate satisfactory out-of-sample prediction results. For example, Dimson and Marsh (1990) show that the improvement of in-sample forecast ability due to data snooping is not transferable to out-of-sample forecasting, similar problems are also presented in White (2000).

The authors propose that this model now be potentially placed on online platforms and be re-trained on a regular basis through constant feed of relevant data by the public. The regression model built for the purposes of this paper is based on the UK periodic survey data. Though the most recent data at the time of writing the paper were used, they are already a few years old. Therefore, by placing this proposed model on public online platforms, live relevant data input can be obtained by the public without running large nationwide surveys, which are both time-consuming and expensive to conduct. By capturing live data, public authorities could process the data instantaneously and take more timely actions based on predicted SWB among citizens.

Another approach might be to link data of the variables in our model which are already available from governmental and public bodies and big data which could be obtained through the use of the Internet of Medical Things (IoMT). Our model is based on several variables, and in fact the majority of data for these variables could be obtained through governmental and public bodies. For example, in the United Kingdom, demographic variables such as age, sex, marital status, income are held by the government such as the Department for Work and Pensions and HM Revenue and Customs (HMRC). Though health-related information, one of the key predictors for SWB, are held by the Department of Health and Social Care, the system cannot track the current and live health status of each patient. Yet variables such as sex, age, and marital status will remain the same, is trackable, or generally do not change frequently, health-related data can vary from one day to another.

Bakker, Aarts, and Redekop (2016) posit that a fundamental challenge of progressing big data analytics within healthcare settings is the availability of sufficient data and that there is a pressing need to integrate and combine big data and other forms of data together. Therefore, though big data analytics has much potential, studies have emphasised that it is ineffective in influencing clinical decisions on its own, and there is a fundamental need to explore methods to help big data analytics attain its real potential. Similarly, Bates, Heitmueller, Kakad, and Saria (2018) cite the increasingly interconnected nature of health and social care systems as a factor and argue the need for integrated data sources in order to support healthcare services.

Thus, our proposal of placing the model on open platforms or cloud could be complemented by the use of the Internet of Medical Things (IoMT) (Byerly et al., 2019; Watts-Schacter & Kral, 2019) which could obtain and process live health-related information through the use of IoT devices such as wearable devices (e.g. smart watch) instantaneously. The health-related data collected through the IoT thus could be linked to the other demographic data held by other government departments in order to predict people's SWB. The recent outbreak of Covid-19 has highlighted that people with pre-existing underlying health conditions were at a higher risk from coronavirus. Thus, further emphasising the importance of being able to effectively monitor and identify people's underlying health conditions, particularly given that older people and people with pre-existing conditions were more at risk than others. In pandemic situations, such as Covid-19, where there are immense pressures on healthcare services, linking the proposed model to IoMT, can possibly allow relevant healthcare authorities to have the ability to track and monitor people's health conditions remotely, therefore enabling healthcare professional to effectively predict people's well-being during troubled times. This might potentially offer a significant transformation of the statistical model derived from cross-sectional survey data into a dynamic training model continuously fed by the public with data, whilst improving its prediction of SWB.

8. Conclusions, limitations and future research

This paper set out to explore the impact of big data by identifying how it can be leveraged to influence well-being. Moreover, a review of the extant literature highlighted the significance of well-being for businesses and the economy as a whole, particularly given the effective management and prediction of well-being can be the difference between, either increasing or decreasing workforce productivity, improving or worsening customer service and satisfaction and reducing or increasing potential future business risks. Accordingly, predictive capabilities relating to SWB has the potential of presenting an array of opportunities for business leaders and policymakers to undertake robust and proactive business-related decisions, through identifying predictive trends relating to an individual's SWB. More specifically, based on the regression models, the paper uncovered that among independent variables, which were selected to predict varying levels of people's perceived well-being, one's marital/co-habiting status was found to be the most powerful predictor for perceived well-being; in this sense those who were not married/cohabiting were more likely to report lower SWB compared with those who were married/co-habiting. Long-term illness was another important predictor that influenced perceived well-being with those with long-term illness being more likely to report lower well-being. Age also played an important role in predicting one's well-being; older people, particularly 66 and above, were more likely to report greater well-being than any other age groups. The paper makes a key contribution to the field given that there has been no survey-based 'big data' framework developed so far.

The Quarterly Labour Force Survey, which forms the basis of the Annual Population Survey employed for this research, runs every quarter. However, by placing the proposed model online, it could gather data on a continuous basis without any additional cost. Furthermore, the prediction output can be processed and obtained instantaneously based on the continuously trained data. Arguably, there are potential drawbacks including ethical issues and personal data security through the IoT (Harbi, Aliouat, Harous, Bentaleb, & Refoufi, 2019; Summer, 2016); however, the potential benefit as a result of the proposed use of the IoT could be significant, thereby identifying and offering support for individuals who need such support most; furthermore, data could be encrypted to avoid any misuse. In this way, a combination of the internet, technology and big data can be used not only to advance the UN SDG 3, but also to support organisational sustainability and economic progress.

From a theoretical stance, this paper has highlighted the link between big data framework, UN SDGs and well-being. From a practical and policy perspective, the paper demonstrates how regression-based predictive analysis can be used for effective decision making to help improve people's well-being. The findings from this study offer valuable insights to policymakers by demonstrating how publicly available big data on citizens provided by themselves can be used to develop policies that improve their lifestyle and well-being.

As with many studies, this paper also has some limitations. More specifically, the authors highlight that the regression analysis was conducted based on a subset of the entire survey sample. For example, the well-being question was only asked from those who were 16 years old or above at the time of the interviews. Furthermore, the APS does not include respondents from Northern Ireland on their religious denominations, which effectively made regression analysis results based on respondents from Great Britain only. In addition, other meaningful variables could have been included in the analysis in order to predict more effectively people's perceived well-being such as the personality of the individual (Carmeli, Yitzhak-Halevy, & Weisberg, 2009) and social networks (Lim & Putnam, 2010). Since the data for our research were sourced from national surveys, such detailed and personal data were not available in the dataset.

In relation to the *logistic regression model for prediction,* it can be argued that significant large samples are required to achieve a high degree of prediction accuracy (Hossain et al., 2002). Our data sample is relatively large, the sample size for the estimation of the model being 179,357, after removing individuals with missing information. The logistic regression model assumes a linear combination of the conditioning variables; low precision of prediction is of no surprise when we count with higher variation in the survey data. Complex models such as machine learning and neural networks are more capable of prediction, these models are now widely used in economics and finance (i.e., Lai, 2014).

Overall, the present research offers a meaningful approach through which SWB can be predicted based on survey data; accordingly, this study provides the foundations upon which further research can be developed, with the view of potentially looking at gathering large data and actually predicting individual subjective well-being through various data sources within a big data framework.

Dataset

Office for National Statistics, Social Survey Division. (2020). *Annual Population Survey, January - December 2017*. [data collection]. *7th Edition.* UK Data Service. SN: 8331, http://doi.org/10.5255/UKDA-SN-8331-6

Office for National Statistics, Social Survey Division. (2020). *Annual Population Survey, January - December 2016*. [data collection]. *7th Edition.* UK Data Service. SN: 8160, http://doi.org/10.5255/UKDA-SN-8160-7

Office for National Statistics, Social Survey Division. (2020). *Annual Population Survey, January - December 2015*. [data collection]. *10th Edition.* UK Data Service. SN: 7928, http://doi.org/10.5255/UKDA-SN-7928-10

Office for National Statistics, Social Survey Division. (2020). *Annual Population Survey, January - December 2014*. [data collection]. *10th*

Edition. UK Data Service. SN: 7684, http://doi.org/10.5255/UKDA-SN-7684-10
Office for National Statistics, Social Survey Division. (2020). *Annual Population Survey, January - December 2013*. [data collection]. *11th Edition*. UK Data Service. SN: 7536, http://doi.org/10.5255/UKDA-SN-7536-11
Office for National Statistics, Social Survey Division. (2020). *Annual Population Survey, January - December 2012*. [data collection]. *9th Edition*. UK Data Service. SN: 7274, http://doi.org/10.5255/UKDA-SN-7274-9
Office for National Statistics, Social Survey Division. (2019). *Annual Population Survey Three-Year Pooled Dataset, January 2015 - December 2017*. [data collection]. *2nd Edition*. UK Data Service. SN: 8370, http://doi.org/10.5255/UKDA-SN-8370-2
Office for National Statistics, Social Survey Division. (2017). *Annual Population Survey, January - December 2011*. [data collection]. *4th Edition*. UK Data Service. SN: 7059, http://doi.org/10.5255/UKDA-SN-7059-4

Appendix A

See Figs. 4–7 and Tables 5–8.

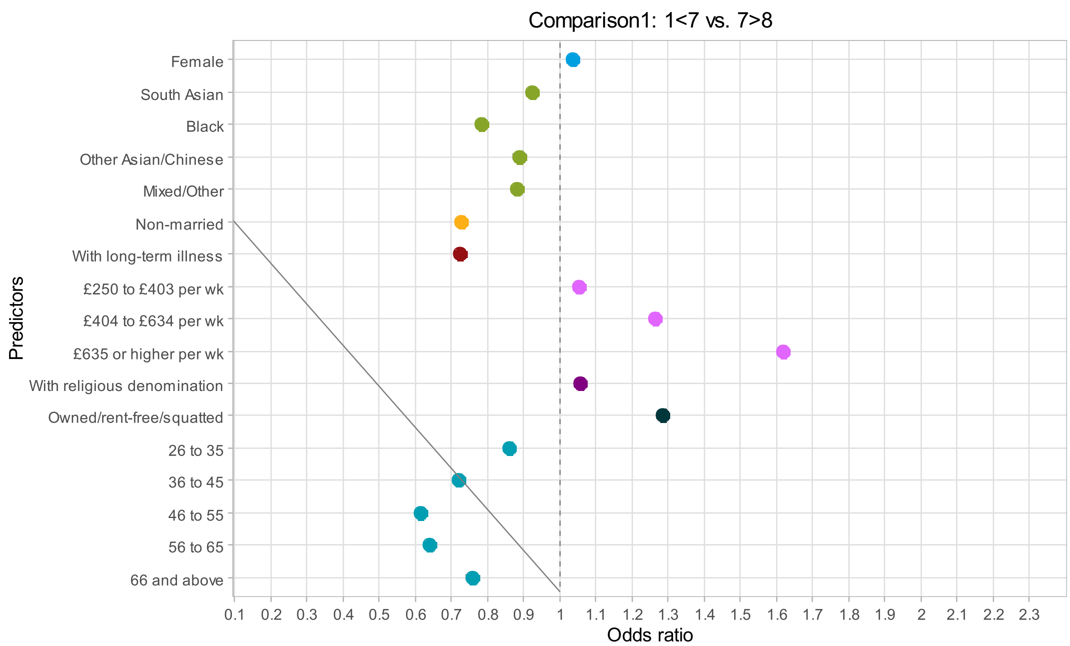

Fig. 4. Odds ratio (95% CIs) Perceived well-being and key demographic characteristics Comparison 1. 1 < 7 w. 7 > 8.

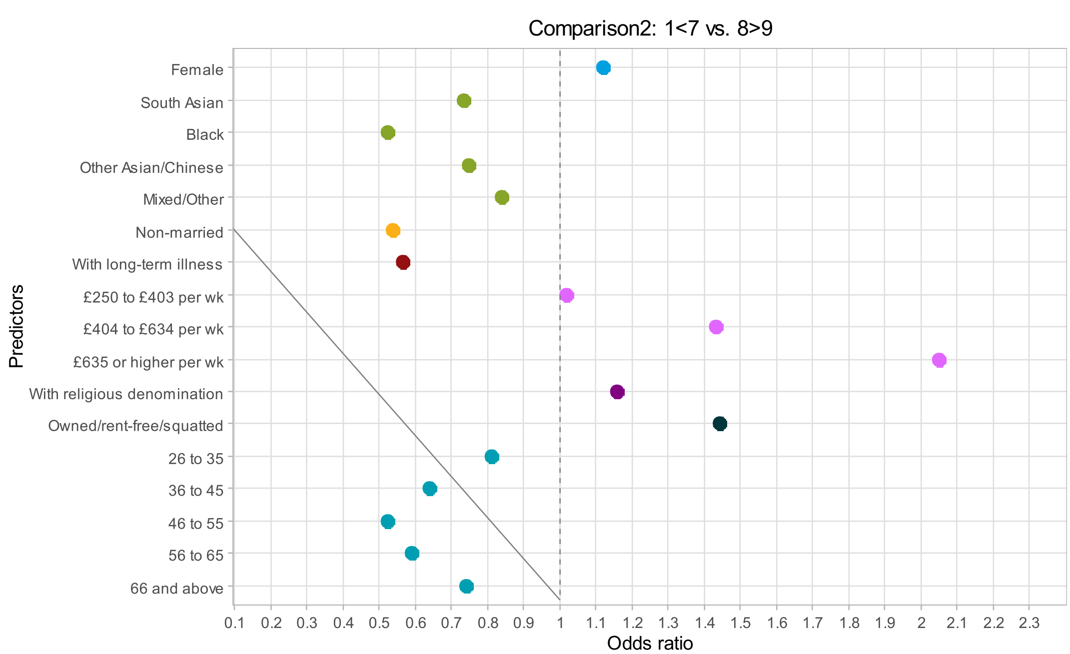

Fig. 5. Odds ratio (95% CIs) Perceived well-being and key demographic characteristics Comparison 2. 1 < 7 w. 8 > 9.

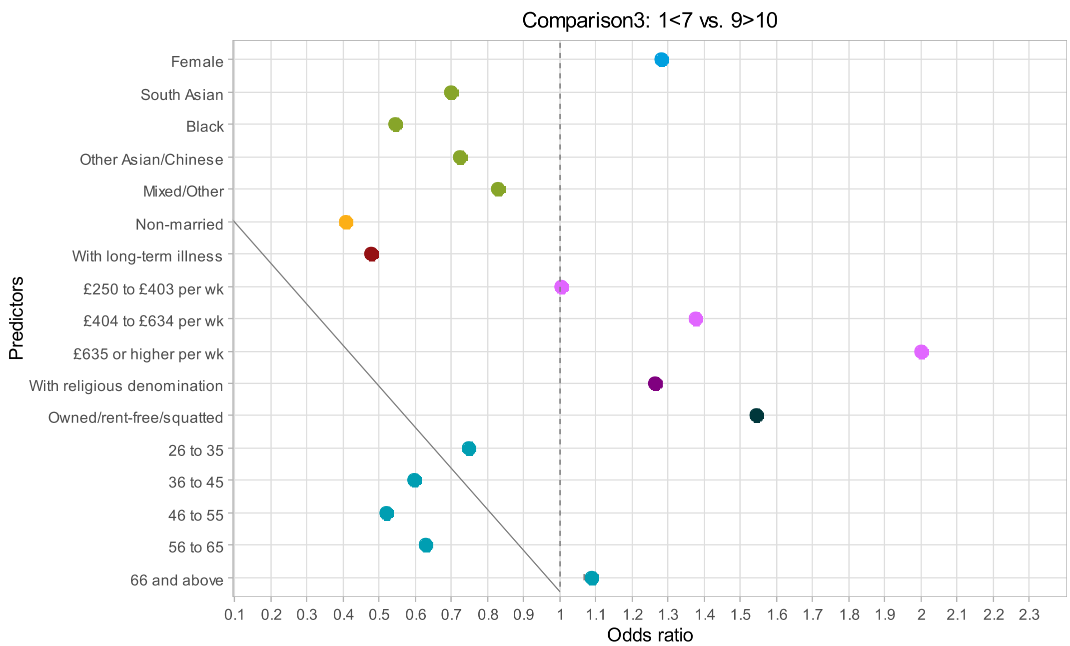

Fig. 6. Odds ratio (95% Cls) Perceived well-being and key demographic characteristics Comparison 3: 1 < 7 w. 9 > 10.

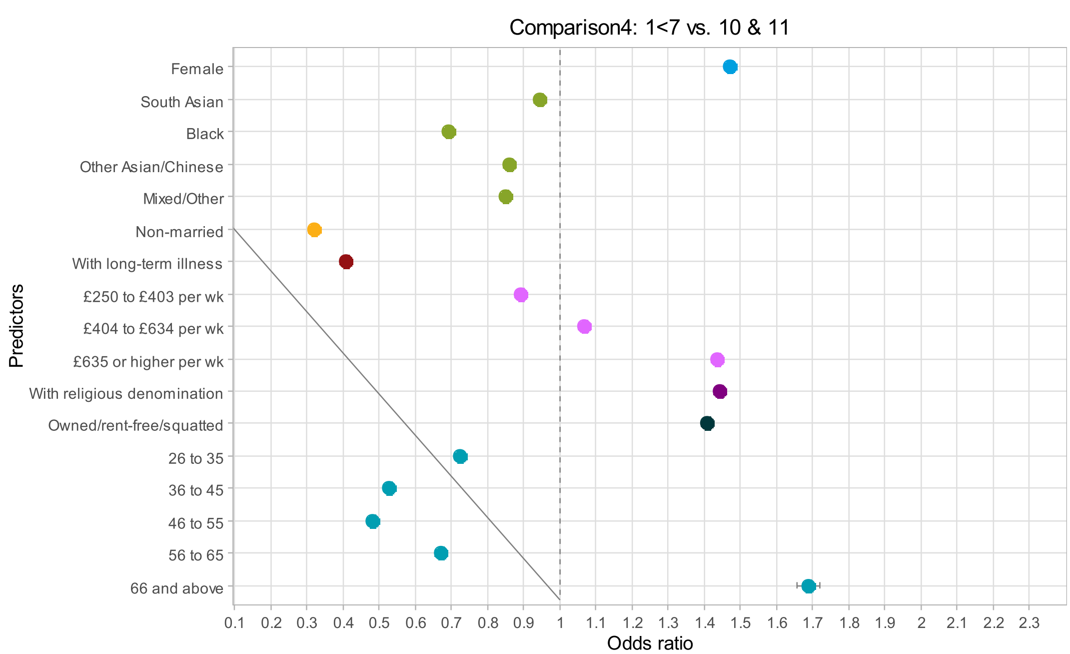

Fig. 7. Odds ratio (95% Cls) Perceived and key demographic characteristics Comparison 4: 1 < 7 vs. 10 & II * Due to confidence intervals being almost identical to odds ratios, confidence intervals are not visible in the majority of the cases.

Table 5
Hierarchical regression – Perceived well-being and selected predictors (Comparison 1: 1 < 7 vs. 7 > 8).

	Model 1							Model 2							Model 3						
	b	*SE*	*t*	*p*	*Low*	*odds ratio*	*High*	*b*	*SE*	*t*	*p*	*Low*	*odds ratio*	*High*	*b*	*SE*	*t*	*p*	*Low*	*odds ratio*	*High*
(Intercept)	0.10	0.00	86.56	0.00	1.10	1.10	1.10	0.47	0.00	116.25	0.00	1.58	1.60	1.61	0.67	0.01	129.40	0.00	1.94	1.96	1.98
Sex (Male as the reference)																					
Female	−0.06	0.00	−38.90	0.00	0.94	0.94	0.95	0.02	0.00	6.54	0.00	1.01	1.02	1.02	0.03	0.00	12.95	0.00	1.03	1.03	1.04
Ethnicity (White as the reference)																					
South Asian	0.01	0.00	3.19	0.00	1.00	1.01	1.02	−0.03	0.01	−3.91	0.00	0.96	0.98	0.99	−0.08	0.01	−12.07	0.00	0.91	0.92	0.94
Black	−0.22	0.00	−56.07	0.00	0.79	0.80	0.81	−0.27	0.01	−44.36	0.00	0.75	0.76	0.77	−0.25	0.01	−40.44	0.00	0.77	0.78	0.79
Other Asian/Chinese	0.17	0.01	27.98	0.00	1.17	1.19	1.20	−0.09	0.01	−9.54	0.00	0.89	0.91	0.93	−0.12	0.01	−12.13	0.00	0.87	0.89	0.91
Mixed/Other	0.04	0.00	9.43	0.00	1.03	1.04	1.05	−0.09	0.01	−11.74	0.00	0.90	0.91	0.93	−0.13	0.01	−16.46	0.00	0.87	0.88	0.89
Married/cohabiting (Yes as the reference)																					
Non-married								−0.29	0.00	−113.86	0.00	0.74	0.75	0.75	−0.32	0.00	−123.16	0.00	0.72	0.73	0.73
Health conditions/illnesses lasting 12 months or more ('No' as the reference)																					
Yes								−0.38	0.00	−149.99	0.00	0.68	0.68	0.69	−0.33	0.00	−125.88	0.00	0.72	0.72	0.73
Weekly gross income (£) (£1 to 249 as the reference)																					
£250 to £403 per wk								0.04	0.00	10.84	0.00	1.03	1.04	1.04	0.05	0.00	15.00	0.00	1.05	1.05	1.06
£404 to £634 per wk								0.21	0.00	58.51	0.00	1.22	1.23	1.24	0.23	0.00	64.88	0.00	1.25	1.26	1.27
£635 or higher per wk								0.42	0.00	109.79	0.00	1.52	1.53	1.54	0.48	0.00	121.48	0.00	1.60	1.62	1.63
Religious denomination (No religion as the reference)																					
With religious denomination								−0.01	0.00	−2.71	0.01	0.99	0.99	1.00	0.05	0.00	20.48	0.00	1.05	1.06	1.06
Accommodation type (Rented/part-mortgage as the reference)																					
Owned/rent-free/squatted								0.19	0.00	71.10	0.00	1.20	1.21	1.21	0.25	0.00	91.64	0.00	1.28	1.29	1.29
Age (16–25 as the reference)																					
26–35															−0.15	0.00	−32.19	0.00	0.85	0.86	0.87
36–45															−0.33	0.00	−69.50	0.00	0.71	0.72	0.73
46–55															−0.49	0.00	−103.92	0.00	0.61	0.61	0.62
56–65															−0.45	0.01	−85.34	0.00	0.63	0.64	0.65
66 and above															−0.28	0.01	−25.21	0.00	0.74	0.76	0.77

* <.05. ** <.01. *** <.001.

Table 6
Hierarchical regression – Perceived well-being and selected predictors (Comparison 2: 1 < 7 vs. 8 > 9).

	Model 1							Model 2							Model 3						
	b	*SE*	*t*	*p*	*Low*	*odds ratio*	*High*	*b*	*SE*	*t*	*p*	*Low*	*odds ratio*	*High*	*b*	*SE*	*t*	*p*	*Low*	*odds ratio*	*High*
(Intercept)	0.87	0.00	908.85	0.00	2.38	2.39	2.39	1.28	0.00	357.73	0.00	3.57	3.60	3.62	1.55	0.00	332.53	0.00	4.68	4.72	4.76
Sex (Male as the reference)																					
Female	−0.10	0.00	−81.48	0.00	0.90	0.90	0.90	0.09	0.00	38.22	0.00	1.09	1.09	1.10	0.11	0.00	48.21	0.00	1.11	1.12	1.13
Ethnicity (White as the reference)																					
South Asian	−0.07	0.00	−21.51	0.00	0.93	0.93	0.94	−0.25	0.01	−42.91	0.00	0.77	0.78	0.79	−0.31	0.01	−52.85	0.00	0.72	0.73	0.74
Black	−0.52	0.00	−145.62	0.00	0.59	0.60	0.60	−0.68	0.01	−121.04	0.00	0.50	0.51	0.51	−0.65	0.01	−114.35	0.00	0.52	0.52	0.53
Other Asian/Chinese	0.09	0.01	15.97	0.00	1.08	1.09	1.10	−0.26	0.01	−29.92	0.00	0.76	0.77	0.78	−0.29	0.01	−33.16	0.00	0.73	0.75	0.76
Mixed/Other	−0.12	0.00	−30.00	0.00	0.88	0.89	0.89	−0.13	0.01	−19.58	0.00	0.86	0.88	0.89	−0.17	0.01	−25.63	0.00	0.83	0.84	0.85
Married/cohabiting (Yes as the reference)																					
Non-married								−0.58	0.00	−254.95	0.00	0.56	0.56	0.56	−0.62	0.00	−268.25	0.00	0.53	0.54	0.54
Health conditions/illnesses lasting 12 months or more ('No' as the reference)																					
Yes								−0.63	0.00	−279.82	0.00	0.53	0.53	0.53	−0.57	0.00	−246.61	0.00	0.56	0.57	0.57
Weekly gross income (£) (£1 to 249 as the reference)																					
£250 to £403 per wk								0.00	0.00	−0.15	0.88	0.99	1.00	1.01	0.02	0.00	6.35	0.00	1.01	1.02	1.03
£404 to £634 per wk								0.32	0.00	102.12	0.00	1.37	1.38	1.39	0.36	0.00	112.24	0.00	1.42	1.43	1.44
£635 or higher per wk								0.64	0.00	184.78	0.00	1.88	1.89	1.90	0.72	0.00	203.09	0.00	2.04	2.05	2.06
Religious denomination (No religion as the reference)																					
With religious denomination								0.07	0.00	32.83	0.00	1.07	1.08	1.08	0.15	0.00	62.73	0.00	1.15	1.16	1.16
Accommodation type (Rented/part-mortgage as the reference)																					
Owned/rent-free/squatted								0.29	0.00	122.03	0.00	1.33	1.33	1.34	0.37	0.00	149.83	0.00	1.44	1.44	1.45
Age (16–25 as the reference)																					
26–35															−0.21	0.00	−49.50	0.00	0.80	0.81	0.82
36–45															−0.45	0.00	−105.23	0.00	0.63	0.64	0.64
46–55															−0.64	0.00	−152.75	0.00	0.52	0.52	0.53
56–65															−0.53	0.00	−113.29	0.00	0.58	0.59	0.59
66 and above															−0.30	0.01	−30.94	0.00	0.73	0.74	0.75

* <.05. ** <.01. *** <.001.

Table 7
Hierarchical regression – Perceived well-being and selected predictors (Comparison 3: 1 < 7 vs. 9 > 10).

	Model 1							Model 2							Model 3						
	b	*SE*	*t*	*p*	*Low*	*odds ratio*	*High*	*b*	*SE*	*t*	*p*	*Low*	*odds ratio*	*High*	*b*	*SE*	*t*	*p*	*Low*	*odds ratio*	*High*
(Intercept)	1.00	0.00	1064.07	0.00	2.72	2.72	2.73	1.35	0.00	378.03	0.00	3.82	3.85	3.88	1.65	0.00	353.89	0.00	5.17	5.21	5.26
Sex (Male as the reference)																					
Female	−0.02	0.00	−18.74	0.00	0.97	0.98	0.98	0.21	0.00	90.14	0.00	1.23	1.23	1.24	0.25	0.00	105.61	0.00	1.27	1.28	1.29
Ethnicity (White as the reference)																					
South Asian	−0.15	0.00	−44.97	0.00	0.86	0.86	0.87	−0.33	0.01	−55.91	0.00	0.71	0.72	0.73	−0.36	0.01	−61.01	0.00	0.69	0.70	0.71
Black	−0.65	0.00	−185.31	0.00	0.52	0.52	0.53	−0.65	0.01	−116.70	0.00	0.52	0.52	0.53	−0.61	0.01	−108.41	0.00	0.54	0.54	0.55
Other Asian/Chinese	0.04	0.01	7.49	0.00	1.03	1.04	1.05	−0.31	0.01	−35.26	0.00	0.72	0.73	0.75	−0.33	0.01	−36.97	0.00	0.71	0.72	0.73
Mixed/Other	−0.24	0.00	−58.64	0.00	0.78	0.79	0.80	−0.16	0.01	−23.80	0.00	0.84	0.85	0.86	−0.19	0.01	−27.45	0.00	0.82	0.83	0.84
Married/cohabiting (Yes as the reference)																					
Non-married								−0.85	0.00	−371.09	0.00	0.43	0.43	0.43	−0.90	0.00	−386.77	0.00	0.40	0.41	0.41
Health conditions/illnesses lasting 12 months or more ('No' as the reference)																					
Yes								−0.78	0.00	−344.50	0.00	0.46	0.46	0.46	−0.74	0.00	−319.20	0.00	0.48	0.48	0.48
Weekly gross income (£) (£1 to 249 as the reference)																					
£250 to £403 per wk								−0.03	0.00	−10.29	0.00	0.96	0.97	0.98	0.01	0.00	1.75	0.08	1.00	1.01	1.01
£404 to £634 per wk								0.25	0.00	81.53	0.00	1.28	1.29	1.30	0.32	0.00	100.81	0.00	1.37	1.38	1.39
£635 or higher per wk								0.58	0.00	169.13	0.00	1.77	1.79	1.80	0.69	0.00	197.35	0.00	1.99	2.00	2.02
Religious denomination (No religion as the reference)																					
With religious denomination								0.18	0.00	80.49	0.00	1.20	1.20	1.21	0.23	0.00	100.85	0.00	1.26	1.26	1.27
Accommodation type (Rented/part-mortgage as the reference)																					
Owned/rent-free/squatted								0.38	0.00	161.43	0.00	1.46	1.46	1.47	0.44	0.00	177.64	0.00	1.54	1.55	1.55
Age (16–25 as the reference)																					
26–35															−0.29	0.00	−67.92	0.00	0.74	0.75	0.76
36–45															−0.52	0.00	−120.62	0.00	0.59	0.60	0.60
46–55															−0.66	0.00	−155.35	0.00	0.51	0.52	0.52
56–65															−0.47	0.00	−100.14	0.00	0.62	0.63	0.63
66 and above															0.08	0.01	8.79	0.00	1.07	1.09	1.11

* <.05. ** <.01. *** <.001.

Table 8
Hierarchical regression - Perceived well-being and selected predictors (Comparison 4: 1 < 7 vs. 10 to 11).

	Model 1							Model 2							Model 3						
	b	*SE*	*t*	*p*	*Low*	*odds ratio*	*High*	*b*	*SE*	*t*	*p*	*Low*	*odds ratio*	*High*	*b*	*SE*	*t*	*p*	*Low*	*odds ratio*	*High*
(Intercept)	0.68	0.00	686.14	0.00	1.97	1.97	1.97	1.12	0.00	298.58	0.00	3.03	3.05	3.08	1.44	0.00	293.65	0.00	4.18	4.22	4.26
Sex (Male as the reference)																					
Female	0.16	0.00	128.46	0.00	1.18	1.18	1.18	0.32	0.00	131.19	0.00	1.37	1.38	1.39	0.39	0.00	155.70	0.00	1.46	1.47	1.48
Ethnicity (White as the reference)																					
South Asian	0.04	0.00	11.42	0.00	1.03	1.04	1.05	−0.06	0.01	−9.72	0.00	0.93	0.94	0.95	−0.06	0.01	−9.36	0.00	0.93	0.95	0.96
Black	−0.55	0.00	−152.79	0.00	0.57	0.58	0.58	−0.44	0.01	−75.36	0.00	0.64	0.65	0.65	−0.37	0.01	−63.65	0.00	0.68	0.69	0.70
Other Asian/Chinese	−0.08	0.01	−13.65	0.00	0.92	0.93	0.94	−0.15	0.01	−16.98	0.00	0.84	0.86	0.87	−0.15	0.01	−16.41	0.00	0.85	0.86	0.88
Mixed/Other	−0.31	0.00	−72.03	0.00	0.73	0.74	0.74	−0.15	0.01	−21.39	0.00	0.84	0.86	0.87	−0.16	0.01	−22.40	0.00	0.84	0.85	0.86
Married/cohabiting (Yes as the reference)																					
Non-married								−1.07	0.00	−436.32	0.00	0.34	0.34	0.35	−1.14	0.00	−455.33	0.00	0.32	0.32	0.32
Health conditions/illnesses lasting 12 months or more ('No' as the reference)																					
Yes								−0.92	0.00	−377.70	0.00	0.40	0.40	0.40	−0.90	0.00	−361.63	0.00	0.40	0.41	0.41
Weekly gross income (£) (£1 to 249 as the reference)																					
£250 to £403 per wk								−0.17	0.00	−55.60	0.00	0.84	0.84	0.85	−0.11	0.00	−35.98	0.00	0.89	0.89	0.90
£404 to £634 per wk								−0.04	0.00	−11.58	0.00	0.96	0.96	0.97	0.07	0.00	19.61	0.00	1.06	1.07	1.07
£635 or higher per wk								0.19	0.00	54.15	0.00	1.21	1.21	1.22	0.36	0.00	98.38	0.00	1.43	1.44	1.45
Religious denomination (No religion as the reference)																					
With religious denomination								0.33	0.00	137.15	0.00	1.38	1.39	1.40	0.37	0.00	148.07	0.00	1.43	1.44	1.45
Accommodation type (Rented/part-mortgage as the reference)																					
Owned/rent-free/squatted								0.30	0.00	122.14	0.00	1.35	1.36	1.36	0.34	0.00	132.25	0.00	1.40	1.41	1.42
Age (16–25 as the reference)																					
26–35															−0.32	0.00	−72.64	0.00	0.72	0.72	0.73
36–45															−0.64	0.00	−141.37	0.00	0.52	0.53	0.53
46–55															−0.73	0.00	−164.34	0.00	0.48	0.48	0.48
56–65															−0.40	0.00	−81.18	0.00	0.67	0.67	0.68
66 and above															0.52	0.01	55.19	0.00	1.66	1.69	1.72

* <.05. ** <.01. *** <.001.

References

Ai, A. L., Park, C. L., Huang, B., Rodgers, W., & Tice, T. N. (2007). Psychosocial mediation of religious coping styles: A study of short-term psychological distress following cardiac surgery. *Personality and Social Psychology Bulletin, 33*(6), 867–882.

Algan, Y., Murtin, F., Beasley, E., Higa, K., & Senik, C. (2019). Well-being through the lens of the internet. *PloS One, 14*(1), Article e0209562. https://doi.org/10.1371/journal.pone.0209562.

Anshari, M., Almunawar, M. N., Lim, S. A., & Al-Mudimigh, A. (2018). Customer relationship management and big data enabled: Personalization & customization of services. *Applied Computing and Informatics, 15*. https://doi.org/10.1016/j.aci.2018.05.004.

Ardelt, M. (2016). Disentangling the relations between wisdom and different types of well-being in old age: Findings from a short-term longitudinal study. *Journal of Happiness Studies, 17*(5), 1963–1984.

Barber, L., Hayday, S., & Bevan, S. (1999). From people to profits (Vol. 355). Brighton, UK: The Institute for Employment Studies. Available at: https://www.employment-studies.co.uk/system/files/resources/files/355.pdf.

Bakker, L., Aarts, J., & Redekop, W. (2016). Is big data in healthcare about big hope or big hype? early health technology assessment of big data analytics in healthcare. *Value in Health, 19*(7). https://doi.org/10.1016/j.jval.2016.09.2058. A705–A705.

Bassi, M., Falautano, M., Cilia, S., Goretti, B., Grobberio, M., Pattini, M., & Delle Fave, A. (2014). The coexistence of well- and ill-being in persons with multiple sclerosis, their caregivers and health professionals. *Journal of the Neurological Sciences, 337*(1), 67–73.

Bates, D. W., Heitmueller, A., Kakad, M., Saria, S., & healthcare. (2018). Why policymakers should care about "big data. *Health Policy and Technology, 7*(2), 211–216. https://doi.org/10.1016/j.hlpt.2018.04.006.

Berry, M., & Linoff, G. S. (1997). *Data mining techniques for marketing, sales and customer support*. John Wiley & Sons.

Blau, D. (1999). The Effect of Income on Child Development. *The Review of Economics and Statistics, 81*(2), 261–276.

Bookwalter, J., & Dalenberg, D. (2010). Relative to whom or what? The importance of relative standing to subjective well-being. *World Development, 38*, 345–355.

Brooks-Gunn, J., & Duncan, G. (1997). The Effects of Poverty on Children. *The Future of Children, 7*(2), 55–71.

Brown, S. L. (2004). Family structure and child well-being: The significance of parental cohabitation. *Journal of Marriage and Family, 66*(2), 351–367.

Byerly, K., Vagner, L., Grecu, I., Grecu, G., & Lazaroiu, G. (2019). Real-time big data processing and wearable internet of medical things sensor devices for health monitoring. *American Journal of Medical Research, 6*(2), 67–72.

Campbell, A., Converse, P. E., & Rodgers, W. L. (1976). *The quality of American life: Perceptions, evaluations, and satisfactions*. New York, NY, US: Russell Sage Foundation.

Capuano, N., Chiclana, F., Fujita, H., Herrera-Viedma, E., & Loia, V. (2018). Fuzzy group decision making with incomplete information guided by social influence. *IEEE Transaction on Fuzzy Systems, 26*(3), 1704–1718.

Capuano, N., Chiclana, F., Herrera-Viedma, E., Fujita, H., & Loia, V. (2019). Fuzzy group decision making for influence-aware recommendations. *Computers in Human Behavior, 101*, 371–379.

Chen, W., & Quan-Haase, A. (2018). Big data ethics and politics: Toward new understandings. *Social Science Computer Review, 38*(1), 3–9.

Carmeli, A., Yitzhak-Halevy, M., & Weisberg, J. (2009). The relationship between emotional intelligence and psychological wellbeing. *Journal of Managerial Psychology, 24*(1), 66–78. https://doi.org/10.1108/02683940910922546.

Chen, H.-C., Chiang, R., & Storey, V. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly, 36*, 1165–1188.

Collins, S., Sun, Y., Kosinski, M., Stillwell, D., & Markuzon, N. (2015). Are you satisfied with life? Predicting satisfaction with life from Facebook. In International conference on social computing, behavioral-cultural modeling, and prediction (pp. 24–33). Springer.

Costa, J., Zonderman, A. B., McCrae, R. R., Cornoni-Huntley, J., Locke, B. Z., & Barbano, H. E. (1987). Longitudinal analyses of psychological well-being in a national sample: Stability of mean levels. *Journal of Gerontology (Kirkwood), 42*(1), 50–55. https://doi.org/10.1093/geronj/42.1.50.

Deaton, A. (2008). Income, health, and well-being around the world: Evidence from the Gallup world poll. *Journal of Economic Perspectives, 22*(2), 53–72.

Deaton, A., & Stone, A. (2013). Economic analysis of subjective well-being: Two happiness puzzles. *AEA Papers and Proceedings, 103*(3), 591–597. https://doi.org/10.1257/aer.103.3.591.

Department for Work and Pensions (2005). Exploring How General Practitioners Work with Patients on Sick Leave, Research Report 257, June. London: Department of Works and Pensions.

Diener, E., & Tay, L. (2012). A scientific review of the remarkable benefits of happiness for successful and healthy living. Report of the Well-Being Working Group, Royal Government of Bhutan. Report to the United Nations General Assembly, Well-Being and Happiness: A New Development Paradigm. Available at: http://www.researchgate.net/profile/Louis_Tay/publication/236272980_A_scientific_review_of_the_remarkable_benefits_of_happiness_for_successful_and_healthy_living/links/54a2e7830cf267bdb9042bb8.pdf.

Diener, E., & Biswas-Diener, R. (2002). Will money increase subjective well-being? *Social Indicators Research, 57*(2), 119–169.

Diener, E., Tay, L., & Myers, D. G. (2011). The religion paradox: If religion makes people happy, why are so many people dropping out? *Journal of Personality and Social Psychology, 101*(6), 1278–1290.

Diener, E., Suh, E. M., Lucus, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin, 125*(March), 276–302.

Diener, E., Tay, L., & Oishi, S. (2013). Rising income and the subjective well-being of nations. *Journal of Personality and Social Psychology, 104*(2), 267–276.

Diener, E. (1984). Subjective well-being. *Psychological Bulletin, 95*, 542–575.

Dimson, E., & Marsh, P. (1990). Volatility forecasting without data-snooping. *Journal of Banking and Finance, 14*(2–3), 399–421. https://doi.org/10.1016/0378-4266(90)90056-8.

Druss, B. G., Schlesinger, M., & Allen, H. M. (2001). Depressive symptoms, satisfaction with health care, and 2-year work outcomes in an employed population. *The American Journal of Psychiatry, 158*, 731–734.

Dunifon, R. E., Ziol-Guest, K. M., & Kopko, K. (2014). Grandparent coresidence and family well-being: Implications for research and policy. *The Annals of the American Academy of Political and Social Science, 654*(1), 110–126.

Easterlin, R. A. (1974). Does economic growth improve the human lot? Some empirical evidence. In P. A. David, & M. W. Reder (Eds.), *Nations and households in economic growth: Essays in Honor of Moses Abramovitz*. New York: Academic Press.

Ellison, C. G., & Fan, D. (2008). Daily spiritual experiences and psychological well-being among US adults. *Social Indicators Research, 88*, 247–271.

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big data consumer analytics and the transformation of marketing. *Journal of Business Research, 69*(2), 897–904.

Evans, M. D. R., Kelley, J., Kelley, S. M. C., & Kelley. (2019). Rising Income Inequality During the Great Recession Had No Impact on Subjective Wellbeing in Europe, 2003–2012. *Journal of Happiness Studies, 20*, 203–228.

Fang, W., Wen, X. Z., Zheng, Y., & Zhou, M. (2017). A survey of big data security and privacy preserving. *IETE Technical Review, 34*(5), 544–560.

Frank E., & Hall, M. (2001). A simple approach to ordinal classification. In L. De Raedt, & P. Flach (Eds.), Machine learning: ECML 2001. ECML 2001. Lecture Notes in Computer Science 2167. Berlin, Heidelberg: Springer.

Friedman, H. S., & Kern, M. L. (2014). Personality, well-being, and health. *Annual Review of Psychology, 65*(1), 719–742.

Frijters, P., Geishecker, I., Haisken-DeNew, J. P., & Shields, M. A. (2006). Can the large swings in Russian life satisfaction be explained by ups and downs in real incomes? *The Scandinavian Journal of Economics, 108*(3), 433–458.

Fujita, H., Gaeta, A., Loia, V., & Orciuoli, F. (2019). Hypotheses Analysis and Assessment in counter-terrorism activities: A method based on OWA and Fuzzy Probabilistic Rough Sets. *IEEE Transactions on Fuzzy Systems*.

Gachet Páez, D., de Buenaga Rodríguez, M., Puertas Sánz, E., Villalba, M. T., & Muñoz Gil, R. (2018). Healthy and wellbeing activities' promotion using a big data approach. *Health Informatics Journal, 24*(2), 125–135.

Glenn, N. D., & Weaver, C. N. (1979). A Note on Family Situation and Global Happiness. *Social Forces, 57*, 269–282.

Goetzel, R. Z., Ozminkowski, R. J., Sederer, L. I., & Mark, T. L. (2002). The business case for quality mental health services: Why employers should care about the mental health and well-being of their employees. *Journal of Occupational and Environmental Medicine, 44*, 320–330.

Goldberg, J. S., & Carlson, M. J. (2014). Parents' relationship quality and children's behavior in stable married and cohabiting families. *Journal of Marriage and Family, 76*(4), 762–777.

Gove, W. R., Style, & Hughes, M. (2016). The effect of marriage on the well-being of adults. *Journal of Family Issues, 11*(1), 4–35.

Graham, C., & Crown, S. (2014). Religion and wellbeing around the world: Social purpose, social time, or social insurance? *International Journal of Wellbeing, 4*(1), 1–27.

Green, M., & Elliott, M. (2010). Religion, Health, and Psychological Well-Being. *Journal of Religion and Health, 49*(2), 149–163.

Hackney, C. H., & Sanders, G. S. (2003). Religiosity and mental health: A meta-analysis of recent studies. *Journal for the Scientific Study of Religion, 42*, 43–55.

Hamid, T. A., Masood Ul Hassan, S., Haron, S. A., & Ibrahim, R. (2018). A systematic review on psychosocial determinants of elderly subjective well-being. *Mediterranean Journal of Social Sciences, 9*(6), 107–120.

Harbi, Y., Aliouat, Z., Harous, S., Bentaleb, B., & Refoufi, A. (2019). A review of security in internet of things. *Wireless Personal Communications, 108*, 325–344.

Hills, T., Proto, E., & Sgroi, D. (2017). Historical analysis of national SWB using millions of digitized books. Working Paper.

Holmgren Caicedo, M., Mårtensson, M., & Roslender, R. (2010). Managing and measuring employee health and wellbeing: A review and critique. *Journal of Accounting & Organizational Change, 6*(4), 436–459.

Horley, J., & Lavery, J. J. (1995). SWB and age. *Social Indicators Research, 34*(2), 275–282.

Hossain, M., Wright, S., & Petersen, L. (2002). Comparing performance of multinomial logistic regression and discriminant analysis for monitoring access to care for acute myocardial infarction. *Journal of Clinical Epidemiology, 55*, 400–406.

Huang, C.-Y. M.-C. H., & Chen, T.-J. (2012). An exploratory study of religious involvement as a moderator between anxiety, depressive symptoms, and quality of life outcomes. *Journal of Clinical Nursing*, (April), 18–24.

Huang, X., Western, M., Bian, Y., Li, Y., Côté, R., & Huang, Y. (2019). Social networks and subjective well-being in Australia: New evidence from a national survey. *Sociology, 53*(2), 401–421.

Jain, P., Gyanchandani, M., & Khare, N. (2019). Enhanced secured map reduce layer for big data privacy and security. *Journal of Big Data, 6*(1), 1–17.

Jee, S. H., O'Donnell, M. P., Suh, I., Kim, I. S., & Korea Medical Insurance Corporation. (2001). The relationship between modifiable health risks and future medical care expenditures: The Korea medical insurance corporation (KMIC) study. *American Journal of Health Promotion, 15*(4), 244–255.

Jeste, D. V., & Harris, J. C. (2010). Wisdom: A neuroscience perspective. *Journal of American Medical Association, 304*(14), 1602–1603.
Johnson, A. D., & Markowitz, A. J. (2018). Food insecurity and family well-being outcomes among households with young children. *The Journal of Pediatrics, 196*, 275–282.
Kahneman, D., & Krueger, A. B. (2006). Developments in the measurement of subjective well-being. *The Journal of Economic Perspectives, 20*(1), 3–24.
Kapteyn, A., Lee, J., Tassot, C., Vonkova, H., & Zamarro, G. (2015). Dimensions of Subjective Well-Being. *Social Indicators Research, 123*(3), 625–660.
Kingdon, G., & Knight, J. (2007). Community, comparisons and SWB in a divided society. *Journal of Economic Behavior and Organization, 64*(1), 69–90.
Kitsaras, G., Goodwin, M., Allan, J., Kelly, M. P., & Pretty, I. A. (2018). Bedtime routines child well-being & development. *BMC Public Health, 18*(1), 1–12.
Koenig, H. G. (2012). Religion, spirituality, and health: The research and clinical implications. *ISRN Psychiatry, 2012*. https://doi.org/10.5402/2012/278730.
Koenig, H. G., & Larson, D. B. (2001). Religion and mental health: Evidence for an association. *International Review of Psychiatry, 13*, 67–78.
Koenig, H., Kvale, J., & Ferrel, C. (1998). Religion and well-being later in life. *The Gerontologist, 28*(1), 18–28.
Koenig, H., King, D., & Carson, V. B. (2012). *Handbook of religion and health*. New York, NY: Oxford University Press.
Kosinski, M., Stillwell, D., & Graepel, T. (2013). Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences*, 201218772.
Krech, S. (2019). Medical big data analytics and smart internet of things-enabled mobile-based health monitoring systems. *American Journal of Medical Research, 6*(2), 31–36.
Kron, M., Grewal, R., Idso, J., Prough, M., Sundaram, C., Klein, S., … Garringer, K. (2019). Mental health indicators in APEC. *International Journal of Social Psychiatry, 65*(2), 92–97.
Lai, H., Hsieh, P., & Zhang, R. (2019). Understanding adolescent students' use of Facebook and their subjective well-being: A gender-based comparison. *Behaviour & Information Technology, 38*(5), 533–548.
Li, B., Ch'ng, E., Chong, A. Y., & Bao, H. (2016). Predicting online e-marketplace sales performances: A big data approach. *Computers & Industrial Engineering, 101*, 565–571.
Lim, C., & Putnam, R. D. (2010). Religion, social networks, and life satisfaction. *American Sociological Review, 75*(6), 914–933. https://doi.org/10.1177/0003122410386686.
Luhmann, M., Schimmack, U., & Eid, M. (2011). Stability and variability in the relationship between SWB and income. *Journal of Research in Personality, 45*(2), 186–197.
MacDonald, L. A. C. (2005). *Wellness at work: Protecting and promoting employee well-being*. London: Chartered Institute of Personnel and Development.
Manning, W. D. (2015). Cohabitation and child well-being. *The Future of Children, 25*(2), 51–66.
Mastekaasa, A. (1994). Marital status, distress, and well-being: An international comparison. *Journal of Comparative Family Studies, 25*, 183–206.
Mayer-Schönberger, V., & Cukier, K. (2013). *Big data: A revolution that will transform how we live, work, and think*. Houghton Mifflin Harcourt.
Mazumder, B., & Davis, J. M. V. (2013). Parental earnings and children's well-being: An analysis of the survey of income and program participation matched to social security administration earnings data. *Economic Inquiry, 51*(3), 1795.
McFadden, S. (1995). Religion and well-being in aging persons in an aging society. *Journal of Social Issues, 51*(2), 161–175.
Menard, S. (1995). *Applied Logistic Regression Analysis*. Thousand Oaks, CA: Sage.
Michael, S. T., Crowther, M. R., Schmid, B., & Allen, R. S. (2003). Widowhood and spirituality: Coping responses to bereavement. *Journal of Women and Aging, 15*, 145–165.
Michalos, A. C. (2017). Education, happiness and well-being. *Connecting the quality of life theory to health, well-being and education*. Cham: Springer.
Michalos, A. C. (1980). Satisfaction and happiness. *Social Indicators Research, 8*, 385–422.
Monroe, B. L., Pan, J., Roberts, M. E., Sen, M., & Sinclair, B. (2015). No! formal theory, causal inference, and big data are not contradictory trends in political science. *PS: Political Science & Politics, 48*(1), 71–74.
Murata, A., Fujii, Y., & Naitoh, K. (2015). Multinomial logistic regression model for predicting driver's drowsiness using behavioral measures. *Procedia Manufacturing, 3*, 2426–2433.
Nazarko, L. (2015). Enabling people to age well. *Nursing and Residential Care, 17*(6), 307.
Ngamaba, K. H., Panagioti, M., & Armitage, C. J. (2017). How strongly related are health status and subjective well-being? Systematic review and meta-analysis. *European Journal of Public Health, 27*(5), 879–885.
Office of National Statistics (ONS), (2011). Measuring subjective wellbeing. London: Office of National Statistics.
Ohlin, L. E., & Duncan, O. D. (1949). The Efficiency of Prediction in Criminology. *American Journal of Sociology, 54*, 441–451.
Othman, A. R., & Fadzil, F. (2015). Influence of outdoor space to the elderly well-being in a typical care centre. *Procedia - Social and Behavioral Sciences, 170*, 320–329.
Palei, S., & Das, S. (2009). Logistic regression model for prediction of roof fall risks in bord and pillar workings in coal mines: An approach. *Safety Science, 47*, 88–96.
Pan, Y., Zinkhan, G. M., & Sheng, A. (2007). The subjective well-being of nations: A role for marketing? *Journal of Macromarketing, 27*(4), 360–369.
Pargament, K. I., & Park, C. L. (1997). In times of stress: The religion-coping connection. In B. Spilka, & D. N. McIntosh (Eds.), *The psychology of religion: Theoretical approaches* (pp. 43–53). Boulder, CO: Westview Press.
Pattani, S., Constantinovici, N., & Williams, S. (2001). Who retires early from the NHS because of ill health and what does it cost? A national cross sectional study. *British Medical Journal, 322*(7280), 208–209.
Piper, A. T. (2015). Sliding down the U-shape? A dynamic panel investigation of the age-well-being relationship, focusing on young adults. *Social Science & Medicine, 143*, 54–61.
Popenoe, D. (2009). Cohabitation, marriage, and child wellbeing: A cross-national perspective. *Society, 46*(5), 429–436.
Ravallion, M., & Lokshin, M. (2002). Self-rated economic welfare in Russia. *European Economic Review, 46*(8), 1453–1473.
Renee Baptiste, N. (2008). Tightening the link between employee wellbeing at work and performance: A new dimension for HRM. *Management Decision, 46*(2), 284–309.
Rhoades, L., & Eisenberger, R. (2001). Affective commitment to the organization: The contribution of perceived organizational support. *Journal of Applied Psychology, 86*(5), 825–836.
Rowe, J. W., & Kahn, R. L. (1997). Successful aging. *Gerontologist, 37*, 433–440.
Ruengtam, P. (2017). Factor analysis of built environment design and management of residential communities for enhancing the well-being of elderly people. *Procedia Engineering, 180*, 966–974.
Ryff, C. D. (2014). Psychological well-being revisited: Advances in the science and practice of Eudaimonia. *Psychotherapy and Psychosomatics, 83*, 10–28.
Saroglou, V., Buxant, C., & Tilquin, J. (2008). Positive emotions as leading to religion and spirituality. *The Journal of Positive Psychology, 3*(3), 165–173.
Shields, M., Wooden, M. (2003) Marriage, children and SWB. In Paper presented at the 8th Australian Institute of Family Studies Conference, Melbourne, February.
Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research, 70*, 263–286.
Slade, T., Johnston, A., Oakley Browne, M. A., Andrews, G., & Whiteford, H. (2009). 2007 National Survey of Mental Health and Well-being: Methods and key findings. *Australian and New Zealand Journal of Psychiatry, 43*(7), 594–605.
Soons, J. P. M., Liefbroer, A. C., Kalmijn, M., & Johnson, D. (2009). The long-term consequences of relationship formation for SWB. *Journal of Marriage and Family, 71*(5), 1254–1270.
Spilka, B., Hood, R. W., Hunsberger, B., & Gorsuch, R. (2003). *The psychology of religion: An empirical approach* (3rd ed.). New York: Guilford Press.
Steptoe, A., Deaton, A., & Stone, A. A. (2015). Subjective well-being, health, and ageing. *The Lancet, 385*(9968), 640–648.
Stevenson, B., & Wolfers, J. (2008). Economic growth and SWB: Reassessing the easterlin paradox. *Brookings Papers on Economic Activity, 2008*(1), 1–87.
Stratton, L., O'Toole, D., & Wetzel, J. (2008). A multinomial logit model of college stopout and dropout behavior. *Economics of Education Review, 27*(3), 319–331.
Summer, S. (2016) You: For Sale: Protecting Your Personal Data and Privacy Online. [Books24x7version]. Available from: http://library.books24x7.com.brad.idm.oclc.org/toc.aspx?bookid=101400. Accessed on 01 May 2020.
The United Nations (2013) International day of happiness: The pursuit of happiness is a fundamental human goal. Available at: http://www.un.org/en/events/happinessday/.
Thiyagarajan, A., Bagavandas, M., & Kosalram, K. (2019). Assessing the role of family well-being on the quality of life of Indian children with thalassemia. *BMC Pediatrics, 19*(1), 1–6.
Tibesigwa, B., Visser, M., & Hodkinson, B. (2016). Effects of objective and subjective income comparisons on subjective well-being. *Social Indicators Research, 128*(1), 361–389.
Truett, J., Cornfield, J., & Kannel, W. (1967). A multivariate analysis of the risk of coronary heart disease in Framingham. *Journal of Chronic Diseases, 20*(7), 511–524.
Veenhoven, R. (1984). *Conditions of happiness*. Dordrecht, the Netherlands: Reidel.
Waite, L. J., & Lehrer, E. L. (2003). The benefits from marriage and religion in the United States: A comparative analysis. *Population and Development Review, 29*, 255–275.
Waldfogel, J., Craigie, T., & Brooks-Gunn, J. (2010). Fragile families and child well-being. *The Future of Children, 20*(2), 87–112.
Watts-Schacter, E., & Kral, P. (2019). Mobile health applications, smart medical devices, and big data analytics technologies. *American Journal of Medical Research, 6*(1), 19–24.
Weaver, M. T., Forrester, B. G., Brown, K. C., Phillips, J. A., Hilyer, J. C., & Capilouto, E. I. (1998). Health risk influence on medical care costs and utilization among 2,898 municipal employees. *American Journal of Preventive Medicine, 15*(3), 250–253.
Westra, D., Wilbers, G., & Angeli, F. (2016). Stuck in the middle? *Health Policy, 120*(4), 345–349.
White, H. (2000). A reality check for data snooping. *Econometrica, 68*, 1097–1126. https://doi.org/10.1111/1468-0262.00152.
Whittington, B. L., & Scher, S. J. (2010). Prayer and SWB: An examination of six different types of prayer. *International Journal for the Psychology of Religion, 20*, 59–68.
Willoughby, B. J., & Belt, D. (2016). Marital orientation and relationship well-being among cohabiting couples. *Journal of Family Psychology: JFP: Journal of the Division of Family Psychology of the American Psychological Association (Division 43), 30*(2), 181–192.
Wilson, W. R. (1967). Correlates of avowed happiness. *Psychological Bulletin, 67*(4), 294–306. https://doi.org/10.1037/h0024431.
Wimberley, D. W. (1984). Socioeconomic deprivation and religious salience: A cognitive behavioral approach. *The Sociological Quarterly, 25*, 223–238.
Wooldridge, J. (2010). *Econometric analysis of cross section and panel data*. London: MIT Press.

World Health Organization. (2017). Suicide fact sheet. Available at: http://www.who.int/mediacentre/factsheets/fs398/en/.

Wiseman, E. (2018) The World's Most Valuable Resource: Not Oil, But Data. [online] Paysafe. Available at: <https://www.paysafe.com/blog/the-worlds-most-valuable-resource-not-oil-but-data/> [Accessed 13 February 2020].

Zhou, Z., Chawla, N. V., Jin, Y., & Williams, G. J. (2014). Big data opportunities and challenges: Discussions from data analytics perspectives [discussion forum]. *IEEE Computational Intelligence Magazine, 9*(4), 62–74.

Vishanth Weerakkody is a Professor of Digital Governance and Dean of the Faculty of Management, Law and Social Sciences at University of Bradford. His current research is multidisciplinary and centred around public sector policy making, process transformation through digital technologies, social innovation, and youth education and skills. His passion for solving societal problems through research, innovation and enterprise has enabled him to secure multiple European and International research grants covering each of these areas. He edits the International Journal of Electronic Government Research, is a Handling Editor for Information Systems Frontiers and acts as conference and track chair in several international conferences dedicated to the field of information systems and digital government research. Before moving to academia, he spent several years working in multinational organisations in the UK and overseas. He draws from over 25 years of industry and academic experience to combine leadership and innovation in technology implementation, adoption and diffusion in society.

Sankar Sivarajah is a Professor in Technology Management and Circular Economy and Head of the School of Management at University of Bradford. His current research interests include exploring the emergent role of digital technologies in the circular economy, information systems evaluation, social innovation and e-Government. He is an investigator of several multi-million-pound R&D projects funded by the European Commission (FP7, H2020, Marie Curie) addressing societal challenges surrounding themes such as Energy Efficient Smart Cities, Green Data Centres, Social Innovation and Participatory Budgeting. He actively publishes in leading peer-reviewed journals such as Journal of Business Research, Information Systems Frontiers, Computers in Human Behaviour and Government Information Quarterly and is also invited member of editorial advisory board of journals. His research has been featured in leading media/trade publications such as Computer Weekly, PublicFinance, UKauthority etc.

Dr Kamran Mahroof is a Lecturer in Supply Chain Analytics and Programme leader for Management and Business Analytics BSc (Hons) at the School of Management, University of Bradford. He has extensive practical experience having worked in various positions for leading companies, most recently for Morrisons PLC, where he led Business Improvement initiatives in Logistics and Supply Chain. His industrial experience has helped shape his research interests, through which he is actively researching in the areas of Supply Chain, Big Data, Circular Economy, and Applied Artificial Intelligence.

Dr Takao Maruyama is a Lecturer at the School of Management, University of Bradford. Prior to joining the School of Management, Takao had gained more than 10 years of industry experience in data analytics. Takao's research interest spans data analytics, information systems, logistics and supply chain management, and other relevant areas which come under the broad research area of quantitative social sciences.

Dr Shan Lu is a Lecturer at the School of Management, University of Bradford. He recently completed his Ph.D. in Finance at the University of Aberdeen in Scotland in January 2019. His main areas of research are empirical finance and applied financial econometrics.