Interdisciplinary Journal of Economics and Business Law, 2023, Vol 12, Special Issue , pp. 37-57

Big Data Approximations: Brand Communities and AI

Gordon Bowen[1], Sebastian Okafor[2], Arshad Jamal[3], Sumesh Dadwal[4] and Hamid Jahankhani[5]

Abstract

The quality of data and information located in brand communities can be ensured by checking for fake reviews or fake information. Artificial intelligence (AI) algorithms have the potential to resolve the ethical issues of fake information and to analyse informational trends accurately and in a timely manner. Thus, the application of AI in brand communities could give firms a sustainable competitive advantage. Also, brand communities extend over many geographical locations, which adds to the richness of the data that could provide valuable insights into products and services. In this application, AI would include an ethical memory and the ability to analyse and synthesise information. Thus, there will be an interface between the algorithm that checks the integrity of the information and the algorithm that analyses the data.

Keywords: Artificial intelligence (AI), brand communities, big data integrity in brand communities, AI and privacy, and ethics and AI.

Introduction

Organisations use social media-based brand communities because brand communities are non-geographically bounded and develop structured social relationships among brand followers (Muniz & O'Guinn, 2001). According to a Statista report (Dixon, 2023), the most popular social media sites ranked by number of (millions) active monthly users in January 2023 were:

Facebook	2,958
YouTube	2,514
WhatsApp	2,000

Instagram	2,000
WeChat	1,309
TikTok	1,051
Facebook Messenger	931
Douyin	715
Telegram	700
Snapchat	635
Kuaishou	626

1. Anglia Ruskin University
2. Cumbria University
3. Northumbria University
4. London South Bank University
5. Northumbria University

The number of active monthly users generates useful information about levels of social interaction. Substantial amounts of data can be generated from social media sites and analysed to reveal worldwide trends.

The global financial crisis from 2007 to 2009 led organisations to seek new customers and they increasingly relied on social media and other digital platforms (Erdogmus & Çiçek, 2012; Kim & Ko, 2012). The geopolitical situation of 2022/23 deepened the need of organisations to use social media and other digital platforms to improve customer reach.

User-generated data (UGD) spread across many geographical locations needs to be analysed accurately and in a timely manner if organisations and their marketeers are to gain the most benefit. Generative artificial intelligence (AI) can quickly find trends in data. However, the transfer of data and information from social media-based brand communities to an AI system must be done with integrity and accountability. How can this be achieved? The aim of this paper is to discuss how data integrity can be safeguarded while maintaining the timeliness and accuracy of the data transfer mechanism.

The article will discuss AI and privacy, then AI, user-generated data (UGD), and big data. The fourth section discusses data integrity and data integrity models. The last two sections discuss implications and present conclusions.

AI and privacy

There are three types of AI. The first type is artificial narrow intelligence (ANI), which is dependent on machine learning. The second type of AI is artificial general intelligence (AGI), which is dependent on machine intelligence; the final type is artificial super intelligence (ASI), which requires machine consciousness. ANI is a specialist application of AI to solve a specific problem (Siri and Alexa are examples). AGI is an intelligent agent that has generalised human cognitive abilities. The last type of AI, namely ASI, would be much smarter than the human brain in practically all fields (Great Learning Team, 2023). AI is encountered every day in many common areas of our life.

The use of personal information in social media networks gives rise to privacy concerns and requires understanding of security issues. Many studies (Zarifis et al., 2021) have highlighted the risk of personal data being compromised on online social media. Privacy issues with social media are linked to identifiability and linking information on social media within the social media setting, the possible recipients, and its potential uses. Preventing identifiability and linkage of personal data is challenging, even if social media sites do not disclose user information. To ensure security, social media users need to address their interpersonal relationships and flexibility in the online environment; for example, social media sites enable users to create a limited profile, such as sharing photos within a personal environment but not with work colleagues. Ahn et al. (2011) argued that social media privacy and security are not fully understood.

AI can be viewed as a catalyst to drive innovation that optimises new products, services, business models, and business ecosystems. The ability of AI to mask complexity and offer value has the potential to bring many benefits to consumers. Humans need assistance to utilise and respond to vast amounts of data and information (Zarifis et al., 2021). However, concerns among consumers about trust and privacy in online transactions (Zarifis et al., 2021) is making regulation unavoidable (European Commission, 2019). Limited trust and privacy concerns about personal information are legitimate barriers for consumers. AI has the potential for consumers to re-evaluate the trust relationship in many areas of their interaction with businesses (Zarifis et al., 2021).

Although AI is a disruptive technology, it brings benefits, such as offering insights and turning insights into action. This is common for many services, including the health sector (Wang & Xu, 2018), and across the whole value chain. Riikkinen et al. (2018) suggested that AI offers insight into optimisation, search and recommendation, and diagnosis and prediction. However, the perspectives of important stakeholders should be considered and incorporated in future AI solutions in the health sector (Zarifis et al., 2021). When AI is applied at the interface between an organisation and a user, and used in evaluation, then it should be revealed to the user (Zarifis et al., 2021); this may pose challenges for AI connectivity in brand communities. AI interactive applications use include big data, blockchain, and internet of things.

The challenge in applying AI depends on the specific type of implementation and the subject area; negative connotations are possible in areas such as individuals' health (He et al., 2019). The risk in using AI is linked to its capabilities and that it may do something that is harmful or make incorrect or inaccurate evaluations (European Commission, 2019). Furthermore, the European Commission (2019) suggested that in a fully automated system mistakes will be implemented directly; thus, humans may act on evaluations that are based on incorrect data or information. The unpredictability of AI raises the issue of control and how to minimise risk. Institutions like the European Union and governments are attempting to regulate AI and offer guidelines on how to minimise risks to consumers in an ethical manner.

van de Heijden (2004) categorised information systems into utilitarian and hedonic systems. Some members of brand communities find brand communities useful because their feedback could lead to improved products and services, and some perceive interacting with brand communities as enjoyable. Based on their research, Davis (1989) and Venkatesh, Thong, and Xu (2016) found that ease of use and usefulness influence adoption of technology across many contexts. The application of AI could improve the ease of use and usefulness of information conveyed to brand communities; for example, virtual personal assistants or chatbots could overcome the complexity of inputting information via a standard computer interface. Information relevant to brand communities could be centralised and operationalised so queries about products or services could be accessed with immediacy. AI can interpret unstructured data such as pictures, diagrams, and emails sent by consumers to brand communities. The ability of AI to process information quickly, make evaluations, and customise responses to consumers' perceived needs will add to the perceived usefulness of brand communities (Zarifis et al., 2021).

Trust is important where there is an exchange in value that involves some risk. The higher the risk the more important is the factor of trust. Purchases online are perceived to involve higher risk than making face-to-face purchases, and trust is a more important mediator (McKnight & Chervany, 2001). Online trust is influenced by the psychology of the consumer and sociological factors. Different consumers' propensity to trust will differ depending on their psychology (Kim & Prabhakar 2004). Current systems used by business have gained sufficient level of public trust, but embedding AI in computer interfaces is an additional risk. Torre et al. (2020) stated that AI is not visible to consumers and the application of AI across the supply chain (front-end and back-end) and the perceived real or imaginary unpredictability of AI leads to a higher level of distrust because the use of AI is not audible or visual.

A model of consumer interaction involves three scenarios: face-to-face purchasing (human evaluation then human interaction), purchasing online (digital evaluation based on human logic then digital interaction) and purchasing online with AI salesperson interaction (AI evaluation then AI interaction) (Zarifis et al., 2021). Additional layers to these scenarios include technology, additional capabilities of technology, and a reduction in the role of humans in the process; this can result in perceptions of increased risks, which can lead to a reduction in trust and an increase in information privacy concerns (McKnight et al., 2011). The hypotheses that follow are (Zarifis et al., 2021:72):

H1: The consumer will have lower trust if the use of AI is visible to them during the process of purchasing health insurance online.

H2: The consumer will have higher perceived information privacy concerns if the use of AI is visible to them during the process of purchasing health insurance online.

Furthermore, the literature suggests that perceived ease of use has a positive relationship with perceived usefulness, trust, privacy concern and the purchase of health insurance (Al-Khalaf & Choe, 2020). Also, perceived usefulness has a positive relationship with the consumer purchase of insurance The remaining hypotheses are (Zarifis et al., 2021:73):

H3: Perceived ease of use will have the same influence on trust in AI if AI is visible during the purchase of health insurance online.

H4: Perceived ease of use will have the same influence on personal information privacy concerns (PIPC) from AI if AI is visible during the purchase of health insurance online.

H5: Perceived ease of use will have the same influence on perceived usefulness of AI if AI is visible during the purchase of health insurance online.

H6: Perceived usefulness will have the same influence on the purchase of health insurance online if AI is visible.

H7: Perceived ease of use will have the same influence on the purchase of health insurance online if AI is visible.

The research by Zarifis et al. (2021) indicates that none of the hypotheses are not supported. AI has a significant influence on decision making by consumers in the online ecosystem and the research on healthcare insurance by Zafaris et al, (2021) will be an important benchmark for AI intervention in online purchasing and the exchange of sensitive information. Zarifis et al. (2021) demonstrated there are varying levels of trust when AI is visible or not visible. Trust is higher without visible AI involvement. Thus, the context is a contributor to the level of trust (Thatcher et al., 2011). Privacy concerns are influenced by the context (Dinev et al., 2015); the use of AI appears to give consumers more concern than other technologies (Park & Shin, 2020).

The implications of the research by Zarifis et al. (2021) suggest the following:

1. Avoid being explicit about using AI unless there is a legal requirement to do so. If there is no legal requirement to do so, then the firm might decide not to be explicit about its use of AI. This might be difficult in practice to achieve when using chatbots.
2. Mitigate the lower trust generated by the use of AI applications, which stems from reduced transparency and explainability. A message about the use of AI at the beginning will help in the mitigation but does contradict point 1. Trust can be built by focusing on user human characteristics (benevolence, integrity, and ability) or system characteristics

(helpfulness, reliability, and functionality) (Lankton et al., 2015).

3. Use positive experiences of AI to mitigate PIPC. Health insurance providers offer assurance and privacy guarantees but do not explicitly mention AI. The assurance could be about how information is shared, used, and securely stored. Included in the assurances are confidentiality, secrecy, anonymity, and the role of AI, such as customer data is used to train AI and all data are anonymised first. Clarity of regulations that protect consumers is essential.

AI, UGD, and big data

Customer needs are many, complex and deep. To cope with the large number a hierarchy of primary and secondary customer needs can be applied. The hierarchy is derived by clustering customer needs based on similarities, but the preferred method is to ask real customers and experts when they are available (Hauser et al., 2023).

Transaction data rarely provide a deep and rich understanding of why a customer is behaving as observed. However, primary data provide a rich understanding, but the collection of the data is time consuming and expensive. UGD is readily available, but scanning websites, feeds, and joining brand communities should be done with permission; thus, the data are selected by the customer (Hauser et al., 2023). There is an expectation that UGD would be biased; however, according to Timoshenko and Hauser (2019) selected data does not create bias in UGD.

UGD analysis using AI could help in identifying and organising customer needs, which would improve product design to meet the wishes of customers; for example, breaking down a product’s attributes and engaging with customers could potentially enable assessment of customers’ preferences. A challenge facing analysis of UGD is the identification of the exact attributes of products from the vast amount of data (Wang et al., 2021). This approach is the core of conjoint analysis (Green et al., 2001). Predicting sales is an important aspect of business; sales is linked to understanding customer needs and preferences, which have business and management implications (Wang et al., 2021). The richness of UGD requires management of social media engagement (Ma et al., 2019).

Brand perception extraction from UGD using AI is an important consideration for organisations and marketers. Dzyabura and Peres (2021) stated that automation of manual processes, such as a marketing research tool, is possible using an AI algorithm. Several researchers have used UGD, such as social media images (Liu et al., 2020) and posts (Pamuksuz et al., 2021), to extract and evaluate brand-related attributes, such as glamorous, rugged, healthy, and fun (Liu et al., 2020) and sincerity, excitement, competence, sophistication, and ruggedness (Pamuksuz et al., 2021). Other methods employed to give a holistic view (a fuller view of the context and user emotions) of brand perception from UGD include Klostermann et al.'s (2018) technique, which considers different online posting environments to discern brand perception in diverse domains and contexts. Thus, this technique helps brands to understand the strengths and weaknesses of their products. Chakraborty et al. (2021) augmented traditional sentiment analysis to supplement the scale of positivity or negativity in users' perceptions of brands. These methods help firms understand the emotions generated by diverse images and characteristics of brands.

Brand positioning assists in differentiating a brand to target customers. Brand positioning help brands to be perceived differently by the target segment, so they are remembered and occupy a unique spot in consumers' perception and consumers purchase the brand repeatedly. Wang et al. (2021) developed an algorithm that allows the comparison of brand position using seven meta-characteristics extracted from large UGD. This enables analysis of UGD data to enrich firms' understanding of market structure that best represents the competitive market (Hauser et al., 2023).

Ma et al. (2019) applied user clusters and an image/posting algorithm that learned from embedded networks. The closer the cluster of user characteristics is to the brand the more likely the users will pin images of that brand. This technique allows firms to match their brand to the right consumer segments. Yang et al. (2021) used a visualisation algorithm to assess user engagement with brands' public fan pages that allows for real-time monitoring and processing of UGD. The algorithm enables the identification of opportunities for brands, such as collaboration with proximal brands in other industries, and threats to brands, such as competitor proximal brands or brands not in the industry but a potential threat. Brands can adjust their market strategy to accommodate changes in the market structure.

UGD can also be used to understand engagement between the user and the brand. Brands use UGD to drive user engagement or predict future user engagement. Li and Xie (2020) found that unstructured data, such as images and videos, induce sharing. Each of the characteristics of an image, such as colour variation, the presence of a human face, or an appearance of professionalism, has a different influence on user engagement depending on the context. “Brand selfies” are selfies posted by users holding a branded product without their face being visible. Brand selfies are more effective at promoting brand engagement and they are more likely to generate likes and comments (Hartmann et al., 2021). Liu, Lee, and Srinivasan (2019) found that UGD play a prominent role in sales when products are expensive, when the number of reviews is modest, when the product market is competitive, and when the products are new. However, branded products are less affected by reviews according to some research (Hauser et al., 2023). The research of Zhang and Luo (2021) suggested that user-generated restaurant photos are strong predictors of restaurants’ survival. They also suggested that UGD has potential in advertising to aid persuasion and communications.

Data integrity

Supervised learning algorithms minimise the loss function by finding a set of parameters that minimise loss thus maximising accuracy with error minimisation achieved by learning algorithm predictor and feedback (Nemoto & Jain, 2020). In traditional supervised learning environments, the feedback is provided by experts in the subject area (Chan & Stolfo, 1998) and trained professionals (Kubat et al., 1998). Data from user-generated content (UGC) and ratings from social networks and ecommerce websites are valuable sources of data (Nemoto & Jain, 2020). The prevalence of these networks and websites sparked the interest of data mining professionals because they offer new datasets and the application of sentiment analysis (Pang & Lee, 2005) and project success prediction (Greenberg et al., 2013). User-generated datasets or user-defined labels could be manipulated leading to user bias and misinformation (Nemoto & Jain, 2020). However, researchers have found that user-generated datasets are of a lower quality than datasets defined by professionals (Riloff et al., 2005; Tsytsarau & Palpanas, 2011). Riloff et al. (2005) noted that sentence meaning can be interpreted differently, for example, explosion in war or terrorist attack has a different meaning from someone exploding because of a disagreement. This inconsistency in interpretation is called attributed noise. According to Nemoto and Jain (2020), inconsistency in the labelling of instances so that similar instances are awarded different labels is called class noise. They suggested that class noise in user-generated datasets has received no attention in the literature.

The reliability of user-defined labels and professional-defined user labels are areas worthy of investigation. Nemoto and Jain (2020) investigated the above concern using two labels, namely, objective user-defined labels and subjective user-defined labels. Research by Sheng et al. (2008) and Bekker and Goldberger (2016) suggested that the performance of a label or classifiers decreases with increasing class noise in the datasets. The major causes of mislabelling in a traditional learning task are subjectivity, data-entry error, or inadequate information to label the instances (Brodley & Friedl, 1999). However, Smyth (1996) suggested that the main cause of subjective labelling errors is when experts disagree, such as medical diagnosis. Brodley and Friedl (1999) suggested that a filtering method would identify mislabelled instances before training a handler. Nemoto and Jain (2020) stated that filtering techniques are effective in handling class noise concerns. However, Bekker and Goldberger (2016) raised concerns about the scalability of filtering techniques and the removal of instances in small training datasets is not always feasible. To overcome the problems, Bekker and Goldberger (2016) developed a probabilistic model that includes true labels of instances as a concealed variable in a deep neural network to learn noise distribution. Active learning requires learners to train from a portion of labelled instances and then query the labelling to improve classification performance in an unlabelled instance (Nemoto & Jain, 2020). Sheng et al. (2008) noted that low quality labelling by non-expert labellers requires quality control processes and that repeated labelling by non-expert labellers, who do not have the necessary knowledge, improves to over 50% labelling accuracy over time, which is enough to maintain the quality of label sets.

Customer rating prediction is notoriously difficult in sentiment analysis, which requires training a text classifier to decide the rating from customer reviews and give an appropriate star rating (generally from 1 to 5) (Pang & Lee, 2005). Nemoto and Jain (2020) assumed that 1 star would be less ambiguous, but 2 and 4 stars would increase the ambiguity and increase the inconsistency of labelled instances. Thus, 1 and 5 stars are easier to identify; therefore, there is less ambiguity and more consistency. Based on an experiment, Nemoto and Jain (2020) found that customers who gave a 4-star rating used positive keywords similar to those used in 5-star customer reviews; thus, the label classifiers (objective and subjective) awarded 40% of 4-star reviews from customers with 5-star ratings. Customers who gave a 2-star rating did not explicitly express their opinion in the review. One-star ratings showed discernible clusters but other star ratings did not. Five-star ratings showed the greatest consistency and highest score (other star ratings had lower scores). Five-star customer ratings had indicative features that lower ratings did not.

Data integrity models

Several solutions have been proposed for cyberthreats (Parast et al., 2022; Beaman et al., 2021). Consumers get news from different sources in real time, such as UGC, and there is a real risk that social media platforms could be abused and disseminate fake news (Ozbay & Alatas, 2020). Fake news is essentially designed to mislead the audience (Shu et al., 2017). The consequence of fake news is stark, for example, the global economic impact of fake news is approximately US$78 billion, with a direct economic loss in the stock market of around US$39 billion (Priority Consultants, 2020).

Is there a binary choice for fake news or authentic news? Many attempts have been made to design detectors of fake news and its dissemination, and there are also fact-checking websites, such as PolitiFact or TruthOrFiction (Shahid et al., 2022). Several models that detect fake news and have the potential to spot fake datasets in brand communities are discussed below.

The aim of the automation detection model is to detect discriminatory features in fake news and classify the different types of concealed features based on a deep learning model; this approach is categorised as automatic detection (Shahid et al., 2022). Ozbay and Alatas (2020) applied a two-step method for identifying fake news on social media. First, unstructured data is converted into structured datasets, which is the preprocessing stage. In the second and final stage they applied 23 supervised AI algorithms to the structured datasets using text mining. This method is suitable for large dimensional data; it is not effective with small datasets that lead to a loss of accuracy. Removal of redundant material from the datasets (they are BuzzFeed Political News, Random Political News and ISOT Fake News) improved the accuracy. A convolutional neural network model (FNDNet) developed by Kaliyar et al. (2020) improved accuracy on precision and recall but it requires huge amounts of data to train the model. However, the dataset is binary and not multilevel (news content, its context, and temporal information) and is known as the hybrid approach.

The early detection model focuses on early detection and dissemination of fake news. The model learns by the application of classifiers when the news is first posted on the internet. Wang et al. (2020) presented the SemSeq4FD model for the early detection of fake news. The model uses enhanced text representation based on graphical representation and pair-wise semantic relations between sentences. SemSeq4FD's precision is 93.90%, accuracy is 93.78%, and it has a recall of 93.78%; however, for the automation detection model FNDNet, precision is 99.40% and recall is 96.88%. Increasing news length impacts the accuracy of the SemSeq4FD model negatively (Shahid et al., 2022; Wang et al., 2020).

The last data integrity model discussed is the feature-based detection model. Many researchers focused on extracting features from fake news to train algorithms to develop classifiers. However, some of the researchers focused on semantics and topological features to develop robust models (Shahid et al., 2022). Schuster et al. (2020) developed a benchmark for the detection of fake news based on large language models that label texts "fake" or "real" according to a truthfulness score. The algorithm achieved an accuracy of 71% for true versus fake news. Results from the benchmarking exercises indicated that manipulation or false texts are more challenging to detect in large language datasets compared to manual or hand-crafted malicious text. Methods that relied on deeper semantic learning used the LIAR dataset by Wang (2017). The accuracy of the two different datasets, Dataset 1 (news articles from Weibo, Twitter, and NewsFN) composition (4180 total, 2100 fake, and 2080 real) and Dataset 2 (news articles from LIAR and KaggleFN) composition (6728 total, 3518 fake and 3210 real) is 91.67% and 92.08%, respectively. Shahid et al. (2022) suggested that the use of deep learning models on small datasets without augmenting the data or without the use of pretrained models may lead to overfitting and thus the algorithm could learn from noise and inaccurate data.

Implications

AI brings many benefits, especially its application to UGD in brand communities; brand communities are geographically unbounded, which enables products and brands to be analysed holistically in different markets with different cultures. The social information generated will give insight into brand perception, positioning, and differentiating products for different markets and industries. However, AI presents challenges, especially in relation to trust and PIPC and how the data will be used. The European Commission (2019) found that informing consumers that AI is being applied in transactions increases the level of trust. However, the expectation that knowing will fully restore the trust construct is not realistic. Nevertheless, informing consumers of the characteristics and purpose of the application of AI will help to create trust and value in relationships. Brand communities must build trust and demonstrate value in their relationships with consumers. Thus, the transaction relationship cannot be simply simplex but move to a duplex mode of value. Firms must demonstrate that the value of the data and information collected from brand communities is beyond marketing and brands, because the datasets help to improve specifications of existing products and services, help innovation, improve customer satisfaction, and increase value. Once consumers have tangible proof that brand communities are about duplex communication, then trust in, and the value of, AI applications in brand communities will be easier to embed. The benefits of AI can only be fully obtained if AI is not only embedded by individual firms, government, and other stakeholders, but by a collectivist societal response. Society can help to build the psychological and sociological constructs necessary to develop trustworthiness and social learning based on positive experiences of AI. Societal responsiveness to the application of AI in brand communities will be dependent on the brand's culture and countries' cultures because brand communities are not bounded geographically. The dispersion of brand communities in different global locales will influence the level of participation, responsiveness, and thus the quality of the data. This might require filtering of the data based on geographical classifiers.

The currency of brand communities is heavily reliant on trust and privacy. Training AI algorithms to detect fake information, reviews, and product and service ratings would enrich the data that firms collect from customer reviews. Thus, AI becomes a moderator of data and information, but this requires openness in the use of AI in the data analytics process and developing a "contract of trust and privacy" with the users of brand communities. The underlying factors that build trust and privacy must be built into the AI algorithm architecture so actions that violate the requirements are barred. AI requires an ethical memory and not just the ability to carry out tasks fast and accurately. However, the ethical memory needs to take account of cultural differences because brand communities extend across many geographical boundaries. An approach in which AI has an ethical memory will underscore the capability of AI to be used ethically; it would be beyond the control of the user and make it more challenging for actors to influence the behaviour of AI, which might build a widespread balanced acceptance of AI, not necessarily a harbour of doom and despair. Obviously, AI can be a force for good or bad, as are many technological innovations, but the application of an ethical memory could shift the balance towards AI as a force for good.

AI will be required to check the integrity of datasets. Are the reviews and scoring fake? The three models discussed that could aid the integrity of datasets all have limitations; however, the application of these models could substantially improve the accuracy of information and scoring, and the analysis of the data would be much quicker, which would help improve product and service specifications in a timely manner. The application of models to analyse a brand community requires that ALL models must be trained to get the most reliable and accurate results. However, the training of the models will need to be done periodically to ensure consistency in outcomes and identification of emerging classifiers. Combining an ethical memory with the analysis of big data will create an integrated algorithm to ensure data integrity and data and information analysis.

Conclusion

Privacy and trustworthiness need to be viewed through different cultural lenses due to the geographical spread of brand communities. Data integrity, and by extension privacy and trustworthiness, can be supported and facilitated by the incorporation of an ethical memory into AI so that hacking of data becomes more challenging in an AI ecosystem. This approach will be a strong counterbalance to the debate on the evil of AI. Datasets need to be managed so that accuracy is consistent and can be relied upon, which will require optimisation of datasets. AI is becoming a pervasive technology and its application to brand communities will help firms to gather data accurately and in a timely manner; thus, this innovation process will provide the effectiveness and operational requirements for firms to deliver products and services based on accurate data and information from customer engagement. The algorithm will combine ethical analysis and data and information analysis.

References

Ahn, G.-J., Shehab, M., & Squicciarini, A. (2011). Security and Privacy in Social Networks. *IEEE Internet Computing*, 15(3), 10-12.

Al-Khalaf, E., & Choe, P. (2020). Increasing customer trust towards mobile commerce in a multicultural society: a case of Qatar. *Journal of Internet Commerce*, 19(1), 32–61. doi:10.1080/15332861.2019.1695179.

Beaman, C., Barkworth, A., Akande, T. D, Hakak, S., & Khan, M. K. (2021). Ransomware: Recent advances, analysis, challenges and future research directions. *Computers & Security*, 111, 1024-90. https://doi.org/10.1109/CCWC57344.2023.10099114

Bekker, A. J., & Goldberger, J. (2016). Training deep neural-networks based on unreliable labels. *IEEE International Conference on Acoustics, Speech and Signal processing (ICASSP).* doi:10.1109/ICASSP.2016.7472164

Brodley, C. E., & Friedl, M. A. (1999). Identifying mislabeled training data. *Journal of Artificial Intelligence Research*, 11 https://arxiv.org/abs/1106.0219

Chakraborty, I., Kim, M., & Sudhir, K. (2021). *Attribute Sentiment Scoring with Online Text Reviews: Accounting for Language Structure and Missing Attributes*. Cowles Foundation Discussion Paper No. 2176. https://dx.doi.org/10.2139/ssrn.3395012

Chan, P. K., & Stolfo, S. J. (1998). Toward scalable learning with non-uniform class and cost distributions: A case study in credit card fraud detection. *Proceedings of the Fourth International Conference on Knowledge Discovery and Data Mining* (pp. 164–168).

Davis, F. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly* 13 (3):319–340. doi:10.2307/249008.

Dinev, T., Albano, V., Xu, H., D'Atri, A., & Hart, P. (2015). Individuals' attitudes towards electronic health records: a privacy calculus perspective. In A. Gupta, V. L. Patel., & R. Greenes (Eds.), *Advances in Healthcare Informatics and Analysis* (pp. 19–50). New York: Springer.

Dixon, S. (2023, Feb 14). *Global social networks ranked by number of users 2023*. Statista. https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/

Dzyabura, D., & Peres, R. (2021). Visual Elicitation of Brand Perception. *Journal of Marketing*, 85(4), 44–66.

Erdogmus, İ. E., & Çiçek, M. (2012). The Impact of Social Media Marketing on Brand Loyalty. *Procedia-Social and Behavioral Sciences*, 58, 1353–1360.

European Commission. (2019). *Ethics Guidelines for Trustworthy AI*. https://digital-strategy.ec.europa.eu/en/library/ethics-guidelines-trustworthy-ai. Access 4th May 2023.

Great Learning Team (2023, Mar 7). *What is Artificial Intelligence in 2023? Types, Trends, and Future of it?* Great Learning. https://www.mygreatlearning.com/blog/what-is-artificial-intelligence/ (accessed 3 May 2023).

Green, P. E., Krieger, A. M., & Wind, Y. (2001). Thirty Years of Conjoint Analysis: Reflections and Prospects. *Interfaces*, 31(3), S56–S73.

Greenberg, M. D., Pardo, B., Hariharan, K., & Gerber, E. (2013). Crowdfunding support tools: predicting success & failure. In M. Beaudouin-Lafon, P. Baudisch, & W. E. Mackay (Eds.), *CHI EA 2013 - Extended Abstracts on Human Factors in Computing Systems*.

Hartmann, J., Heitmann, M., Schamp, C., & Netzer, O. (2021). The Power of Brand Selfies. *Journal of Marketing Research*, 58(6), 1159-1177. https://doi.org/10.1177/00222437211037258

Hauser, J. R., Li, Z., & Mao, C. (2023). Artificial Intelligence and User-Generated Data Are Transforming How Firms Come to Understand Customer Needs. In K. Sudhir, & O. Toubia (Eds.), *Artificial Intelligence in Marketing* (pp. 147-167). Emerald Publishing Limited, Bingley. https://doi.org/10.1108/S1548-643520230000020007

He, J., Baxter, S. L., Xu, J., Xu, J., Zhou, X., & Zhang, K. (2019). The practical implementation of artificial intelligence technologies in medicine. *National Library of Medicine*, 25(1), 30–36. doi: 10.1038/s41591-018-0307-0

Kaliyar, R. K., Goswami, A., Narang, P., & Sinha, S. (2020). FNDNet–a deep convolutional neural network for fake news detection, *Cognitive Systems Research*, 61, 32–44.

Kim, A. J., & Ko, E. (2012). Do Social Media Marketing Activities Enhance Customer Equity? An Empirical Study of Luxury Fashion Brand. *Journal of Business Research*, 65(10), 1480-1486.

Kim, K. K., & Prabhakar. B. (2004). Initial trust and the adoption of B2C E-commerce. *Data Base for Advances in Information Systems*, 35(2), 50–64. doi:10.1145/1007965.1007970

Klostermann, J., Plumeyer, A., Böger, D., & Decker, R. (2018). Extracting brand information from social networks: Integrating image, text, and social tagging data. *International Journal of Research in Marketing,* 35(4), 538–56.

Kubat, M., Holte, R. C, & Matwin, S. (1998). Machine learning for the detection of oil spills in satellite radar images. *Machine Learning*, 30, 195–215.

Lankton, N., McKnight, H., & Trip, J. (2015). Technology, humanness, and trust: rethinking trust in technology. *Journal of the Association for Information Systems*, 16(10), 880–918. doi:10.17705/1jais.00411.

Li, Y., & Xie, Y. (2020). Is a Picture Worth a Thousand Words? An Empirical Study of Image Content and Social Media Engagement. *Journal of Marketing Research*, 57(1), 1–19.

Liu, L., Dzyabura, D., & Mizik, N. (2020). Visual Listening In: Extracting Brand Image Portrayed on Social Media. *Marketing Science*, 39(4), 669–686.

Liu, X., Lee, D., & Srinivasan, K. (2019). Large-Scale Cross-Category Analysis of Consumer Review Content on Sales Conversion Leveraging Deep Learning, *Journal of Marketing Research*, 56(6), 918 – 943, https://doi.org/10.1177/0022243719866690

Ma, L., Sun, B., & Zhang, K. (2019). Image network and interest group – A heterogeneous network embedding approach to analyze social curation on Pinterest, PinterestNetworkEmbedding_MaSunZhang_2019.pdf (utoronto.ca)

McKnight, H., Carter, M., Thatcher, J. B., & Clay, P. (2011). Trust in a specific technology: an investigation of its components and measures. *ACM Transactions on Management Information Systems*, 2(2), 1-25.

McKnight, H., & Chervany, N. L. (2001). What trust means in E-commerce customer relationships: an interdisciplinary conceptual typology. *International Journal of Electronic Commerce*, 6(2), 35–59. doi:10.1080/10864415.2001.11044235

Muniz, Jr., A. M., & O'Guinn, T. C. (2001). Brand Community. *Journal of Consumer Research*, 27(4), 412-432.

Nemoto, K., & Jain, S. (2020). A Pitfall of Learning from User-generated Data: In-depth Analysis of Subjective Class Problem. *Procedia Computer Science*, 185, 160–169. https://doi.org/10.1016/j.procs.2021.05.017

Ozbay F. A., & Alatas, B. (2020). Fake news detection within online social media using supervised artificial intelligence algorithms. *Physica A: Statistical Mechanics and its Applications*, 540, 123174.

Pamuksuz, U., Yun, T. T., & Humphreys, A. (2021). A Brand-New Look at You: Predicting Brand Personality in Social Media Networks with Machine Learning. *Journal of Interactive Marketing*, 56, 55–69.

Pang, B., & Lee, L. (2005) Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales. *Proceedings of the 43rd Annual Meeting of the Association for Computational Linguistics* (ACL05), 115–124.

Parast, F. K, Sindhav, C., Nikam, S., Yekta, H. I., Kent, K. B., & Hakak, S. (2022). Cloud computing security: A survey of service-based models. *Computers & Security*, 114, 1025-1039. 10.1109/TCSS.2022.3177359

Park, Y. J., & Shin, D. (2020). Contextualizing privacy on health-related use of information technology. *Computers in Human Behavior*, 105, 106204–106209. doi: 10.1016/j.chb.2019. 106204.

Priority Consultants (2020, August 11). *Fake news and its impact on the economy*. [Online]. Available: https://priorityconsultants.com/blog/fake-news-and-its-impact-on-the-economy/ Accessed 12th June 2023.

Riikkinen, M., Saarijärvi H., Sarlin, P., & Lähteenmäki, I. (2018). Using artificial intelligence to create value in insurance. *International Journal of Bank Marketing*, 36(6), 1145–1168. doi:10.1108/IJBM-01-2017-0015.

Riloff, E., Wiebe, J., & Phillips, W. (2005). Exploiting subjectivity classification to improve information extraction. *AAAI'05: Proceedings of the 20th National Conference on Artificial Intelligence*, 3, 1106–1111.

Schuster, T., Schuster, R., Shah, D. J., & Barzilay, R. (2020). The limitations of stylometry for detecting machine-generated fake news. *Computational Linguistics*, 46(2), 499-510.

Shahid, W., Jamshidi, B., Hakak, S., Isah, H., Khan, W. Z., Khan, M. K., & Choo, K.-K. R. (2022). Detecting and Mitigating the Dissemination of Fake News: Challenges and Future Research Opportunities. *IEEE Transactions on Computational Social Systems*, 99, 1–14. DOI: 10.1109/TCSS.2022.3177359

Sheng, V., Provost, F., & Ipeirotis, P. G. (2008). Get Another Label? Improving Data Quality and Data Mining Using Multiple, Noisy Labelers. *NYU Working Paper No. 2451/25882*. SSRN. Available at: https://ssrn.com/abstract=1281348

Shu, K., Sliva, A., Wang, S., Tang, J., & Liu, H. (2017). Fake news detection on social media: A data mining perspective. *ACM SIGKDD Explorations Newsletter*, 19(1), 22–36.

Smyth, P. (1996). Bounds on the mean classification error rate of multiple experts. *Pattern Recognition Letter*, 17(12), 1253-1257. https://doi.org/10.1016/0167-8655(96)00105-5

Thatcher, J. B., McKnight, H., Baker, E. W., Ergun Arsal, R., & Roberts, N. H. (2011). The € role of trust in postadoption IT exploration: an empirical examination of knowledge management systems. *IEEE Transactions on Engineering Management*, 58(1), 56–70. doi: 10.1109/TEM.2009.2028320.

Timoshenko, A., & Hauser, J. R. (2019). Identifying Customer Needs from User-Generated Content. *Marketing Science*, 38(1), 1–20.

Torre, I., Goslin, J., & White, L. (2020). If your device could smile: people trust happy-sounding artificial agents more. *Computers in Human Behavior*, 105, 106215. doi:10.1016/j.chb.2019.106215.

Tsytsarau, M., & Palpanas, T. (2011). Survey on mining subjective data on the web. *Data Mining and Knowledge Discovery*, 24, 478–514.

Van der Heijden, H. (2004). User Acceptance of Hedonic Information System *MIS Quarterly*, 28(4), 695-704. http://dx.doi.org/10.2307/25148660

Venkatesh, V., J. Y. L. Thong, and X. Xu. 2016. Unified theory of acceptance and use of technology: a synthesis and the road ahead. *Journal of the Association for Information Systems* 17 (5):328–376. doi:10.17705/1jais.00428.

Wang, Y. (2017). "Liar, liar pants on fire": A new benchmark dataset for fake news detection. *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics* (Volume 2: Short Papers). https://aclanthology.org/P17-2067.

Wang, X., He, J., Curry, D. J., & Ryoo, J. H. (2021). Attribute Embedding: Learning Hierarchical Representations of Product Attributes from Consumer Reviews. *Journal of Marketing,* 86(6), 155-175. 00222429211047822.

Wang, Y., Wang, L., Yang, Y., & Lian, T. (2020). SemSeq4FD: Integrating global semantic relationship and local sequential order to enhance text representation for fake news detection. *Expert System Applications,* 166, 114090. doi: 10.1016/j.eswa.2020.114090.

Wang, Y., and W. Xu. 2018. Leveraging deep learning with LDA-based text analytics to detect automobile insurance fraud. Decision Support Systems 105:87–95. doi:10.1016/j.dss. 2017.11.001.

Yang, Y., Zhang, K., & Kannan, P. K. (2021). Identifying Market Structure: A Deep Network Representation Learning of Social Engagement. *Journal of Marketing*, 86(4), 37–56. https://doi.org/10.1177/00222429211033585

Zarifis, A., Kawalek, P., & Azadegan, A. (2021). Evaluating If Trust and Personal Information Privacy Concerns Are Barriers to Using Health Insurance That Explicitly Utilizes AI, *Journal of Internet Commerce*, 20, 1, 66-83.

Zhang, M., & Luo, L. (2021, October 28). *Can Consumer-Posted Photos Serve as a Leading Indicator of Restaurant Survival? Evidence from Yelp*. SSRN. https://dx.doi.org/10.2139/ssrn.3108288