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Between Knowledge Gain and Ethical Responsibility

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Learning Objectives
- Understand the theoretical intuition behind ethics
- Illustrate the spectrum of data science ethics
- Explain how ethics influence data science in tourism
- Discuss the pitfalls of not taking an ethical perspective into account

1 Introduction

Wherever data is used to predict and support decision-making processes, those decisions can affect people in many ways (Barocas & Selbst, 2016). Although the growing field of data science has brought many new possibilities for problem-solving and developing new insights based on data analysis (Saltz & Dewar, 2019), the topic of ethical challenges and the "appropriate" way of using data has only recently been starting to receive the attention it deserves. Since an overall

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compliance in regard to what is considered ethical vs. unethical seems to be lacking (Asadi-Someh et al., 2016), the field of data science requires a more thorough investigation. The idea of ethics involves not only human rights but also the rights of data derived from people as well as how to best handle this abundance of information for the greater good. By having a closer look at recent literature involving ethics within various sectors and branches of data science, this chapter aims at providing an overview of the ethical challenges that are currently being faced and discussed.

2 Ethics

Ethics can be defined as the science of morals or the moral evaluation of choices (LaFollette, 2007; Ulrich, 2008). Its most foundational interpretation “refers to the perception of something being good or right” (Saltz & Dewar, 2019, p. 198). In the context of data science, ethics illustrate the right, proper, acceptable, and socially appropriate approach to conducting research with this type of data.

Ethics can be divided into the different categories of meta-ethics, normative ethics, and applied ethics. While meta-ethics describe ethical theories, normative ethics focus on the process of reaching moral conclusions. Applied ethics are concerned with their practical application in certain contexts (Mingers & Walsham, 2010). Furthermore, ethics are based on three major ethical philosophies: the Kantian approach (Louden, 1986), the utilitarian point of view (Shaw, 1999), and the virtue model (Slote, 1992) of ethics. The Kantian approach involves honesty and responsibility and the belief that every ethical action’s foundation revolves around moral values, whereas the utilitarian approach looks for outcomes and consequences (LaFollette, 2007). The virtue model is not concerned with consequences or ethical actions but, rather, with subjective nonrational impulses (instincts) that influence how people act when clear rules are not present (Hursthouse, 1999; Merrill, 2011).

The Kantian approach (or deontology) is focused on the act itself instead of its consequences and results. “Actions are to be seen as morally right or wrong, just or unjust, in themselves regardless of their consequences” (Mingers & Walsham, 2010, p. 835). Hence, the outcome can never justify the means (in contrast to the utilitarian perspective). Kant’s philosophical approach is connected to duty and responsibility towards others and aims to universalize an ethical act for all humans. Nevertheless, the approach is criticized for being highly individually focused and limited in its universal application across different culture and belief systems (LaFollette, 2007; Mingers & Walsham, 2010).

The utilitarian standpoint, or, consequentialism, is based on choosing actions with the best overall outcomes while simultaneously minimizing any harm (origins: David Hume and Adam Smith). However, utilitarianism is limited by its power of predicting outcomes due to many unpredictable factors. Moreover, the approach is criticized for maximizing benefits for the majority while often marginalizing and ignoring minorities and/or justifying unmoral means for the greater good (LaFollette, 2007; Mingers & Walsham, 2010; Saltz & Dewar, 2019).

Lastly, virtue ethics, as defined by Hursthouse (1999), is "agent-centered" rather than "act-centered" and emphasizes virtues and moral character in comparison to rules or duties (deontology) or consequences (utilitarianism). Although this viewpoint dates back to Plato and Aristotle, it has recently been revived; virtue ethics imposes the question of what sort of person one should/would like to be and is based on the fundamental concepts of 'the good' and the virtues of mind and character.

2.1 Data Science and Ethics

Ethics in data science can be viewed within the general context of computing and has been deliberated on ever since its development in the 1950s. A broader discourse was first initiated during the 1980s–1990s, leading to the introduction of the term "applied ethics." As a result, computer ethics have been adopted into various curricula, textbooks, conferences, journals, and academic literature (see Stahl et al. (2016) or Brey and Soraker (2009) for more details) (Saltz & Dewar, 2019).

However, ethics in the field of data science have only recently been added to the ongoing debate. While ethics in general focus on humans' decisions and choices, ethics in data science are more occupied with algorithm decisions (Mittelstadt et al., 2016). Algorithms and their parameters are specified by developers with certain results and outcomes in mind, thus prioritizing specific values over others (Kraemer et al., 2011; Nakamura, 2013). "At the same time, operation within accepted parameters does not guarantee ethically acceptable behaviour" (Mittelstadt et al., 2016, p. 1). Overall, good algorithms depend on good data and it is significant to note that algorithms have the same limitations as all data-processing methods. Algorithms, however, have often been found to be as biased as humans when it comes to minorities. Data can often inherit prejudices and reflect biases that exist as a whole in society, hereby making it challenging to identify the problem's original source (Barocas & Selbst, 2016). Ethics in data science thus aim to provide guidance on how to interpret data and, as a consequence, what actions to implement (Mittelstadt et al., 2016).

In the context of current findings on ethical considerations in data science, Saltz and Dewar (2019) conducted a systematic literature review by inserting the search terms "data science and ethics," "big data and ethics," "data science and ethical," and "big data and ethical" into six electronic databases. After applying the defined exclusion criteria, a total of 80 papers were reviewed by means of content analysis, and four key ethical themes were identified. First of all, findings revealed (1) the need for an ethics framework containing a consensus regarding terminology as well as a set of detailed regulations and policies (in contrast to a more general code of ethics). Furthermore, (2) the newness of the field concerning "ethical implications that have not been previously considered by others or even been highlighted as a potential ethical dilemma" (Saltz & Dewar, 2019, p. 202) was placed into the spotlight. The third key theme revealed (3) data-related challenges, as for instance, privacy and anonymity issues, data misuse, and data accuracy and validity. Finally, (4) model-related challenges concerning personal and group harm, subjective model designs, and model misuse and interpretation issues encompassed the fourth key theme. These results present a bigger picture of the dispute surrounding data science and ethics. It is, however, significant to examine specific ethical issues further; thus, the following sections aim to address certain problems in a more detailed manner.

3 Data Science Ethics Issues

3.1 Privacy

Privacy rights serve as a frame for the amount of unstructured data available and the general protection of personal data and information (Schermer, 2013). In particular, privacy issues are concerned with the level of control users have in regard to their personal data, the ownership of data rights as well as the accessibility of data under which circumstances (Mateosian, 2013; Saltz & Dewar, 2019). In addition, privacy issues deal with the process of data collection, the use of the respective data, conclusions that derive from the data and actions that are taken as well as the consequences thereof (Birrer, 2005). However, while the costs of data protection have increased, the costs and barriers concerning privacy issues have decreased due to enhanced algorithms and larger datasets (Fairfield & Shtein, 2014).

Data privacy is one of the most critical issues, not only for data science but also for governments and lawmakers worldwide. For issues related to data protection and security, the following four areas can be classified (van den Hoven, 2008): (1) Protection against information-based damage, such as identity theft or fraud, due to the vulnerability of personal data in possession of parties wanting to impose harm. (2) Safeguard against informational inequality, focusing on the vulnerability of consumers themselves and their lack of knowledge or understanding that their personal data is accessible to businesses or governments (without any transparency about how these parties use this data). (3) Security involving informational injustice, which protects the use of consumers' data for causes and reasons outside the circumstances agreed upon (e.g., medical data that is accessed during the process of a job application). (4) Protection revolving around moral autonomy and moral identification concerning the rights of individuals to not be observed or controlled through their data and to create a certain distance between the outside world and the individuals themselves.

Generally, data science researchers mostly work with data that is readily available to them, and, oftentimes, they can derive and predict sensitive and personal data from already existing and accessible data (Kosinski et al., 2013; Mayer & Mutchler, 2014). A study by Mayer and Mutchler (2014) analyzed phone metadata and revealed that not only the users' identities but also their occupations, religious affiliations, or even medical conditions could be extracted. Another quite controversial study, testing the effect of emotional contagion on social media, revealed how easy it is to access Facebook data and manipulate content without the user's awareness thereof (Kramer et al., 2014). In addition, Kosinski et al. (2013) showed that by analyzing users' Facebook likes, sensitive and personal attributes (e.g., sexual orientation, ethnicity, personality traits, age, and drug use) could be predicted. Hence, despite users' cautiousness of not revealing certain information about themselves, other data can be used to put these missing pieces together. While accessing and predicting personal data touches upon the issues of privacy, it is also significant to emphasize that the use and application of this data (e.g., for advertising purposes) can potentially result in unprecedented consequences on an individual level (e.g., advertisements and flyers for maternity products can reveal an unwanted pregnancy) (Kosinski et al., 2013).

These studies and examples demonstrate that individuals who leave traces of information online can easily be identified and categorized. In fact, big data is not necessarily required as connecting metadata from a few traces of online data is sufficient to program algorithms to derive even more information (Ananny, 2016). The issue of accessing information in such a simple manner can be compared to the problematic nature of surveillance. A "surveillance system obtains personal and group data in order to classify people and populations according to varying criteria, to determine who should be targeted for special treatment, suspicion, eligibility, inclusion, access, and so on" (Lyon, 2003, p. 20). In a bigger context, this "social sorting" of data can lead to discrimination and long-term social differences (Lyon, 2003).

While existing laws and regulations address the potential risks of protecting individual rights, they fail to focus on data protection, particularly when it comes to protecting groups of people from the impact of invasive data processing. Not only are users mostly unaware of the fact that certain data has been collected from them, but decision-makers often use big data analysis to make choices that can hugely impact either groups or individuals. In addition, these decisions are not based on data of an individual but, rather, on data that categorizes an individual as a member of a certain group. As a result, this process often leads to misrepresentation, discrimination, or bias. Hence, privacy and data protection are essential to safeguard personal rights and interests as well as to maintain the quality of society as a whole (Mantelero, 2016).

Whether or not privacy and data protection are regulated by the law, the issue of ethics remains. Moreover, regardless of certain data mining algorithms and data processes being legal, it does not necessarily mean they are ethical, especially when the respective individuals are not asked for permission (Custers, 2013). However, when talking about data in general, and data access in particular, there will always be a trade-off between privacy and security as well as control and freedom (Newell & Marabelli, 2015). "Ethics can only attempt to specify extreme boundaries of definitely unacceptable outcomes, and at the meta-level it can try to specify when the negotiation process is fair" (Birrer, 2005, p. 213).

3.2 Data Validity

Errors in data analysis may not only lead to a lack of validity but may also result in ethically problematic results with far-reaching consequences. As data form the foundation for decisions and indicate options for action, any errors that occur during the data collection, input, or processing steps can prompt results in the wrong direction (Lever et al., 2016). On the one hand, the results may appear incomprehensible or difficult to interpret, contributing to false conclusions. Worse still, they can have fatal consequences for the individual as well (Balas et al., 2015). For example, Amazon faced massive problems with an AI solution for their internal recruiting due to using a machine learning algorithm that was biased towards women. The historical training data, which served as input for the algorithm, was distorted by the male-dominated working environment of the technical world, thus discriminating against women (Vincent, 2018). Along similar lines, women were also widely discriminated against when it came to Apple's credit card. Even though both sexes were professionally equivalent, the credit line for men was set at up to 20 times the level of women (Vincent, 2019).

When it comes to issues in data science, they mainly occur in three simplified forms and may be caused by (1) a lack of validity of the data itself (Balas et al., 2015), (2) shortcomings in data processing (Kwon et al., 2014), or (3) a lack of validity concerning the created models (Raschka, 2018).

1. *Lack of validity of the data*

   When working with publicly available data and using it as a basis for calculations, it is especially important that the data quality is sufficient (Gao et al., 2016). Often, however, quality checks and opportunities to gain a closer look into how the data was created are not possible (Gao et al., 2016). Another problem is the choice of a representative sample as researchers are often confronted with limitations and can only work with the data that is available to them (Seely-Gant & Frehill, 2015). In the introductory chapter on Natural Language Processing (see chapter "Natural Language Processing (NLP): An Introduction"), Twitter posts were used as sample data. Compared to Instagram or Facebook data, Twitter posts are easy to obtain and are, therefore, a frequently used source to analyze public opinions (Dindar & Yaman, 2018). Twitter users are typically younger, more technically savvy, and tend to have higher income, but they also vary greatly across countries (Dindar & Yaman, 2018; Seely-Gant & Frehill, 2015). In addition, an analysis of Twitter data revealed that only a small, very specific part of the population can be characterized as opinion leaders (Seely-Gant & Frehill, 2015). Hence, it should be questioned as to how representative this data is of the entire population and what conclusions can ultimately be made when relying on the analysis results of such data.
2. *Lack of data processing*

   A lack of data processing often happens due to unfavorable decisions (Kwon et al., 2014), especially since there are numerous approaches that deal with missing values (Ngiam & Khor, 2019). Moreover, there are certain procedures that react very sensitively to the presence of missing values and algorithms that can handle missing values well (Pratama et al., 2016). Hence, the question of whether missing data should simply be deleted, replaced with the mean or median, interpolated from adjacent data points, or simply be kept remains. Another example can be seen in the context of text analysis; in regard to dealing with irony and sarcasm or phrases that were automatically created by bots, the researcher must think about how to best handle text elements and must decide if the text can always be taken at face value (Potamias et al., 2020).

3. *Lack of validity of created models*

   When it comes to the selection of features for machine learning (see chapter "Feature Engineering"), this process is of utmost importance (Cai et al., 2018). One must keep in mind which features are available in general and which ones should ultimately be selected in order to train a model. In machine learning, the quality of the training data itself also plays a decisive role (Raschka, 2018). If one trains a model using data from the past and the actual data used in the model is different from the original training data, the results will lead to skewed and misleading conclusions. Furthermore, customer behavior or economic data can change over time and lead to incorrect forecasts if the model does not adapt to these changes (Dergiades et al., 2018). For example, a prediction involving travel data from the last few years, especially from the time period during the COVID-19 pandemic, would massively distort the result in most cases. However, a badly trained algorithm that incorporates these outliers would be even worse than a one-time false result.

   Besides the features, the selection of the appropriate model must also reflect an ethical perspective (Lever et al., 2016). The researcher should take into account if the model has been evaluated accordingly, if there is a possibility of over- or underfitting the data, and if the correct hyperparameters have been tuned (see chapter "Hyperparameter Tuning"). Which model should ultimately be chosen? In any case, it would be unethical to choose a model that has been rendered inaccurately but best fits the context's goals (Raschka, 2018). Besides mistakes that can occur, be it from carelessness or ignorance, many subjective decisions, which can also lead to serious consequences, must be made by the researcher even during the structured processes of data science projects (Kitchin, 2014). It is therefore important to handle data and models responsibly, coupled with an awareness of the consequences of the decisions made.

3.3 Algorithm Fairness and Bias

Although data mining and other data science methods are designed to eliminate human bias, algorithms can only be as good as the data it was supplied with (Barocas & Selbst, 2014). "If data miners are not careful, the process can result in disproportionately adverse outcomes concentrated within historically disadvantaged groups in ways that look a lot like discrimination" (Barocas & Selbst, 2014, p. 673). Data mining is highly dependent on the quality of the data; yet, often the data inherits prejudices and biases represented in society or performed in the past. In fact, algorithms can adopt these prejudices without even being programmed to do so. Hence, discrimination can either be a result of biased data or the data mining process itself. Such cases of unintentional discrimination are especially difficult to identify and mitigate (Barocas & Selbst, 2014).

While data mining algorithms can be used to detect spam or fraud (e.g., flag spam e-mail) as mostly uncontroversial binary categories, decisions about the creditworthiness or integrity of an employee, for example, cannot be uncovered so easily and depend largely on pre-defined categories and target variables specified by the data miner. Thus, the problem lies mostly in the definition of the (often subjective) class labels in addition to the possible inaccurate classification. In this way, various choices of defined class labels result in different consequences and impact certain classes (Barocas & Selbst, 2014; Gandy, 2010; Hildebrandt & Koops, 2010).

Another potential area of algorithm bias results from the actual training of the data that machine learning works with. Biased training data can lead to discriminatory models. Hence, in situations where biased cases are used as training data, the problem ends up repeating and reproducing itself. On the other hand, if the bias lies in the sample, the algorithm will repeat, eventually putting the underrepresented population at a disadvantage. Both cases can affect the training data, the algorithm, the results, and, in turn, its derived implications (Custers, 2013).

In addition, the training data and algorithm can adopt biases based on user or consumer behavior. Results from a study by Sweeney (2013) show that Google is more likely to display keyword-triggered ads of arrest records for search terms involving "black-sounding" names in comparison to "white-sounding" names. Furthermore, the study found that the reason for these results is Google's algorithm to predict the likelihood that users will click on a certain advertisement based on historical user data. In this fashion, the algorithm learns (from the data) which ads receive the most hits and further promotes those accordingly, whereby the biased search results replicate themselves.

If the bias lies in the data itself, it can be a result of incorrect, incomplete, or non-representative datasets or data that has no records of certain classes of people, for instance, due to a lack of resources to collect this type of data (English, 2009; Tufekci, 2014; Wang & Strong, 1996). In particular, certain classes of people who live on the margins of big data may be underrepresented in the data or simply omitted completely (Lerman, 2013). "Not all data is created or even collected equally, there are 'signal problems' in big-data sets — dark zones or shadows where some citizens and communities are overlooked or underrepresented" (Crawford, 2013).

4 Big Data

When it comes to big data, it seems that the notion of "one-size-fits-all" must be discarded since the use of multidisciplinary big data affects both privacy and confidentiality and poses dilemmas in various ways, depending on the circumstances of a certain situation (Steinmann et al., 2016; O'Leary, 2016). This also leads to the question of whether big data and analytics should belong to the computer ethics category or if they should be treated as completely separate aspects (O'Leary, 2016). Although computer ethics has been a popular topic over the past decades and most experts are aware of these ethical guidelines (Saltz & Dewar, 2019), O'Leary (2016) argues that existing frameworks lack the specificity for certain technologies, thus limiting their effectiveness when applied to big data.

Furthermore, despite the availability of developed codes of conduct for big data projects, such as the IEEE Ethics and Member Conduct, the Data Science Code of Professional Conduct, or the Code of Ethics for Certified Analytics Professionals, to name but a few, the actual purpose for which the data is being used as well as the field in which the data scientists/analysts work lead to complications regarding which particular code to adhere to (O'Leary, 2016). Fairfield and Shtein (2014) additionally highlight the fact that big data techniques do not pair well with ethical approaches from the social sciences as they tend to focus strongly on individual human participants. Therefore, it seems that multiple policies or codes of ethics need to be designed explicitly for various big data techniques, technologies, and applications. In this way, researchers and organizations would also gain a clear-cut perspective and understanding of what kind of ethical behavior is expected and how the data can be handled (O'Leary, 2016).

According to Steinmann et al. (2016), big data analysis presents two main ethical concerns: the fact that big data tend to deal with populations rather than individual samples and that big data can be reused, repurposed, recombined, and reanalyzed (4R challenge). One speaks of reusing when the data is used for other purposes within the same domain in addition to what it was initially collected for (Steinmann et al., 2016). Based on the misconception that publicly available data does not impose any further harm, Metcalf and Crawford (2016) state that this ethical risk relating to individuals and communities is continuously overlooked in the field of big data. Here, it is significant to review the conditions of the initial dataset and to argue who, in such a case, is genuinely responsible for the various outputs (Leonelli, 2016).

On the other hand, repurposing involves taking the original data and using it for unrelated purposes (e.g., outside of the intended domain) in which the validity of the analysis as well as privacy and protection contexts both pose potential issues (Steinmann et al., 2016). An additional dilemma concerning a privacy breach also occurs in the case of combining and recombining data. Not only does recombining data potentially lead to uncovering an individual's stripped identification, but the project's underlying goal may even be to purposely involve the act of re-identifying a person. Lastly, reanalysis deals with big data archives that are stored for longitudinal reasons, especially within the healthcare and public health sectors (Steinmann et al., 2016). All in all, the topic of 4R and privacy ultimately boils down to "where consent often amounts to an unread terms of service or a vague privacy policy" (Metcalf & Crawford, 2016, p. 2) and the management thereof.

Another pressing issue when it comes to big data is the topic of human subjects themselves. In Mittelstadt and Floridi's (2016) meta-analysis, 11 key themes were revealed. These include, amongst others, informed consent, anonymity and data protection, ownership, and epistemology. Despite these topics being crucial, one downfall of strict data protection and distribution rights is potentially missing out on opportunities. Due to the prevention of sharing specific datasets, some researchers may end up not having access to the data they need and the information that would theoretically be appropriate and acceptable to use in the right context (Mittelstadt & Floridi, 2016; Choudhury et al., 2014). Nevertheless, it is argued that the exaggeration of the benefits of big data has masked the notion of taking ethical implications and considerations seriously, making it even more challenging to manage sensitive data. Additional future issues that have received little attention in the literature and require further investigation involve "group-level ethics, ethical implications of growing epistemological challenges [see chapter 2] [...], effects of Big Data on fiduciary relationships, the ethics of academic versus commercial practices, ownership of intellectual property derived from Big Data, and the content of and barriers to meaningful data access rights" (Mittelstadt & Floridi, 2016, pp. 468–469).

Educational research is another sector in which big data and ethics come together as a matter of contention. Daniel (2019) believes that the future application of big data in education will eventually cause complications regarding student safety and security within and across institutions. Major concerns embody themes such as maintaining research integrity and providing data to institutions without one's permitted consent to share amongst third parties (Daniel, 2019). In this case, both national and international standards need to be set in order to address ethical issues in the field of education. As big data and ethics can be seen in many other sectors and subject matters (e.g., public health, healthcare, journalism, etc.) as well, it is crucial to consider the various branches in which data science is being incorporated and to start thinking about integrating methodological, societal, and ethical issues into an interdisciplinary approach (Delpierre & Kelly-Irving, 2018).

5 Artificial Intelligence and Machine Learning

As with so many technologies, the goal of Artificial Intelligence (AI) developers is to solve some of the complex issues of humanity and change the world for the better. Another vision is to overcome human subjectivity and let a system that is not influenced by emotions or personal biases judge with principles of fairness. However, the biggest challenge of AI is combining these principles with the nature of human need and instruction. Another aspect is that AI, similar to any other intelligent technology, can also be used by humans to harm other humans or even act autonomously in destructive ways (Gabriel, 2020). Based on the three laws of robotics developed by Isaac Asimov in the 1940s/1950s, researchers and humanity as a whole must conquer the "new" challenge of adjusting and expanding these laws to the way AI is used today as well as the way AI will be used tomorrow and in the near future (Asimov, 1950).

The combination of big data and AI, along with the subfield of machine learning, accompany each other in numerous ways. In the public health sector, this can consist of medical screening, vision augmentation, and epidemiological and psychological matters, amongst others (Benke & Benke, 2018). Nonetheless, the question of ethical issues in the context of health is a big topic for big data to tackle. Benke and Benke (2018), for example, view genetic privacy and the balance between public rights and law enforcement to be a controversial subject. Moreover, they believe that algorithmic transparency (e.g., free of bias; explanatory rather than predictive) should be part of an ethical standard. Brady and Neri (2020) agree, stating that the knowledge of deep learning and the way algorithms are developed and used can lead to ethical concerns or abuses. This is especially significant when algorithms are applied to risk detection and prediction. Therefore, algorithms should be tested intensively in order to be able to withstand potential biases and false negatives (Linthicum et al., 2018). Yet, the question then remains: who is responsible for the future lives that are lost?

The large number of publications on the situation of COVID-19 in the field of tourism is also currently bringing more health-specific issues into perspective and giving them new relevance. In this regard, "ethical issues arise in terms of ownership of data, how data are used, and how the privacy of those from whom the data is derived is protected" (Brady & Neri, 2020, p. 232). Here, the importance of anonymizing data arises as patient re-identification can bring about unwanted advertising or even lead to medical records being brought forward to the public (Brady & Neri, 2020). Other ethical issues include topics such as resource inequality, liability, conflicts of interest, and workforce disruption. Overall, a framework for AI, not only within the health and medical sectors, should be deemed necessary in order to protect human rights, foster user safety, discuss the roles of future diagnosticians and medical specialists, and raise awareness of the risks of AI tools (Benke & Benke, 2018; Brady & Neri, 2020).

In addition, AI faces two principal challenges: technical and normative. The technical challenge focuses on ensuring the reliability of artificial agents to fulfill the tasks they are expected to achieve (Gabriel, 2020). Normative challenges, on the other hand, concentrate on the alignment of human values and principles to avoid unsafe and unreliable outcomes (Gabriel, 2020). Nevertheless, the possibility of imitation-learning of an AI system from a moral expert reveals the deeper underlying problem concerning ethics and brings up questions if moral experts even exist in this framework as well as who can be called a moral expert and by whom (Gabriel, 2020; MacIntyre, 2013; McDowell, 1979; Vallor, 2016). In addition, Gabriel (2020, p. 6) raises the following questions: "From what data should AI extract its conception of values, and how should this be decided? Should this data include everyone's behaviour, or should it exclude the behaviour of those who are manifestly unethical (sociopathic) or unreasonable (fundamentalists)? Finally, what criteria should be used for determining which agent is the 'most moral', and is it possible to rank entities in this way?" Different frameworks have already been developed to define such principles and rules for a more responsible and ethically designed AI (see Future of Life Institute, 2017; Montreal Declaration, 2017; IEEE, 2017; European Group on Ethics in Science and New Technologies, 2018; Floridi et al., 2018; Partnership on AI, 2018). However, more work must be done in order to establish a universal consensus regarding a consistent framework of the ethical development and usage of AI.

As society becomes more and more dependent on technology, and when it comes to AI and machine learning in other domains, the biggest concerns remain in regard to data privacy and data security. For instance, Mageswaran et al. (2018) emphasize the need to scrutinize data that derive from personal apps and highlight the establishment of ethical algorithms in the business field. The use of AI tools could not only lead to technologies deliberately intruding on people's lives but also to revealing or preventing a crime; therefore, coinciding with law and ethics policies is of utmost importance (Soroka & Kurkova, 2019). Durante (2019), in addition, says that society needs "to deal with the social (ethical, legal, economic, and political) impact of the delegation of decisions [in regard] to automated systems and autonomous artificial agents" (p. 372). Based on what is already known, the best way to face ethical dilemmas in light of data science is to review every situation thoroughly and question whether or not the data and ethics have been used appropriately within the established context (Saltz & Dewar, 2019).

6 Conclusion

In order to gain knowledge and subsequently derive recommendations for actions and decisions, the use of structured and unstructured data with the aid of data science methods and procedures has increased significantly both in academic research and in business-related situations. Tourism can be seen as a social phenomenon, which is why the analysis of people and their behavior is often put in the foreground. Thus, tourism-specific research and data are usually embedded in a social context and therefore linked to complex and sensitive ethical issues. However, such issues are much broader than the often superficially discussed topics of privacy, security, identity, trust, responsibility, and ownership (Longbing, 2019).

In addition to the data itself, the processing and analysis, along with the use of suitable algorithms and the development of models, right up to the interpretation and utilization of the results can all give rise to massive ethical pitfalls, especially since the application of data science approaches has only recently started to gain importance in the tourism industry. While certain sectors, such as online travel agencies (OTAs), are strategically aligning themselves with data science, destinations and the hospitality sector are only slowly starting to address this topic. As in any other industry, there is a sense of optimism and excitement about the new opportunities to make more and more data-driven decisions. However, at the beginning, the understanding as well as the correct assessment of the relevance of ethical aspects often remain on the back burner. Only when new achievements have been consolidated and established is there time to optimize processes and take issues such as ethics into account. Theoretically, though, this process should be the other way around, and this applies to academic research as well. It seems as if the new possibilities of gaining knowledge often lead to a rash decision of incorporating methods without thinking twice about the ethical requirements, applications, and/or consequences beforehand. Therefore, one can only hope that a solution to this problem will be recognized and enforced at all levels and that individuals become aware of the fact that ignoring ethical aspects corresponds to a short-sighted view of endangering not only others but also oneself.

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