Implementing Ethical Issues into the Recommender Systems Design Using the Data Processing Pipeline

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Abstract—**Applying information systems within a business process requires a good understanding of the expected benefits, system requirements as well as of the effects that the process change will have on its actors and stakeholders. Integrating machine learning based systems (MLS) into a business process requires an even broader focus on potentially affected users and stakeholders. Leading to changes in the process, but also in the user and stakeholder behavior, ethical values are directly influenced by the decisions taken during the data processing stages within system development. In this paper, a scenario of an MLS, a fictional recommender system for food delivery, is used to identify potential ethical issues that occur during the composition and usage of the artifact. Data centered analysis of the system development is applied to identify, which ethical values are mostly affected in each data processing stage. It is argued that even when the used data for MLS is not originated from an individual, and thus is not necessarily subject to privacy regulations, ethical analysis and socially-aware engineering of the information system are still required. Suggestions what ethical aspects can be implemented into the design of the MLS are derived here based on the presented scenario. The effects of MLS application in a business process are furthermore briefly outlined for every stage of data processing. Using this scenario-based approach allows identification of social and technical aspects that can be affected by the application of MLS in business context.**

Keywords- socio-technical systems; machine learning based systems design; ethical values; ethical analysis; business process.

I. INTRODUCTION

The challenge of the integration of ethical issues in the information systems design has been specifically laid out by Levina in [1].

The pervasiveness of algorithmic systems in our daily lives is stimulating public and research debate about their potential effects on the individual behavior and also on the society as a whole. Several companies and governmental initiatives react to this development by publishing ethical principles on how their Information Technology (IT) artifacts that involve Machine Learning (ML) components are created, leading to the so called "principle proliferation" [2]. Evidently, Information Systems Research (ISR) should manifest its leading role in pursuing practices for the creation of IT artifacts that are not only technically innovative but also socially acceptable.

This paper provides a contribution by presenting and discussing the outcomes of the ethical analysis of a paradigmatic case of a Machine Learning-based System (MLS) application. Here, an MLS is an Information and Communication Technology (ICT) that is composed of one or more algorithms working together and capsuled into one or more executable software components [3]. The ethical analysis demonstrates what ethical values are affected the most in which data processing stage. These insights allow software developers and system architects to focus the introduction of socio-technical activities accordingly. The results of the applied analysis approach lay the ground for theoretical development of a mixed methods approach that is focused on ethical reasoning in ISR and engineering of socio-technical systems [4].

The presumption of this mixed methods approach is, that ethical compliance of an IT-system is an integral part of the design process, as well as the product use. The linkage to ethical questions and the design of an IT artifact can be historically established in several ways. First of all, the core of the engineering activities, such as software engineering and IT systems design, is the solution to the design problem [5]. Since there are multiple possibilities to solve a problem, (software) engineers weight one alternative against another. The decision criteria for the design alternatives can be financial restrains, user requirements and functional fit of the alternatives. Once the chosen alternative is realized as an artifact, it will have good and bad effects. Hence, one obvious moral obligation of a (software) engineer in the role of the solution creator is to pick a design alternative that does not induce harm [5]. Thus, to create an IT system that takes into account the effects of its application on the business processes, users, as well as the effected parties, theses potential effects need to be taken into account in its design [4][5]. It is e.g., the case, when digital systems such as a recommender or a digital assistant system provide a service for its user.

A service, in the physical world, as well as digital, comes with costs that are not only monetary. It entails partial loss of autonomy in the realm it is being offered. User accepts the service if the assessed amount of the autonomy loss is acceptable and thus the user provides consent to this loss by agreeing to use the service instead of performing the offered function him- or herself. The engagement with the service can furthermore be associated by the user with loss of autonomy due to opaque processes of result generation. Social reluctance of these practices is evident. Only 19% of surveyed users of digital services believe that tech companies design their services with people's best interests in mind and

47% feel they have no choice but to sign up to services despite having concerns [8].

Identifying and complying to ethical issues in the MLS design can thus enable autonomous decisions for the user within the interaction with the service. In addition, this quality can provide a distinctive feature on the market of IT products.

Following this reasoning, the goal of this research is to expand the present literature on potential ethical issues of MLS. The structure of the paper follows this reasoning. An example scenario is presented in Section V using the data process centered ethical analysis [7] described in Section IV and requirements of socio-technical system design in Sections II and III. Suggestions about how the identified ethical issues in Section VI can be integrated into the IT system are provided in Section VII. Using the offered scenario, the process and supplementary effort to include these aspects into the artifact design can be assessed by the system designer or business engineer, providing an actionable radius to create socially acceptable IT products, as well as to lay the ground for future research questions. Conclusion and outlook on the future work finish the paper.

II. State of the art in Socio-technical aspects of recommender systems

Socio-technical systems are described via Baxter and Sommerville [4] as systems that involve a complex interaction between humans, machines and the environmental aspects of the work system. Machine learning-based systems incorporate this interaction already in their input, i.e., the data from which patterns are derived and test data sets for the mathematical models are the result of an interaction between a human and a business information system. Thus, their implementation into the organizational processes has an intermediate effect on the actors on the outside and inside of the organization. Specifically, in this context, socio-technical considerations are not just a factor within the systems development process, but they have to be considered at all stages of the development life-cycle.

For MLS the system development life-cycle includes data processing. Data processing is furthermore divided into phases of data collection, data processing, model definition, model training and calculation of the results. The socio-technical factors are triggered when the MLS results are implemented into a business process, requiring a human decision or a decision that concerns human actors. To catch these challenges the ALTAI principles were established by the European Commission [9] to help evaluate a socially aware MLS design. These are: Participation, Transparency, Human Autonomy and Auditability. These principles are considered here as facilitators for the software design approach that focuses on the person affected by the software result rather than the direct user of the software.

Identifying ethical issues that might occur during the system design allows conclusions on the ethical values that are affected in different stages of system design. This activity is considered here the first step of the incorporation of these values into the design of a socially-aware information system. Hence, a scenario for an MLS, a recommendation application, is described Section V and used to demonstrate an approach to identifying ethical issues.

III. Overview of the state of the art of Ethical analysis approaches for recommender systems

Ethical issues in the context of IT-artifacts have gained increasing attention in research over the last decade. Paraschakis [10][11] explores e-commerce recommender applications and suggests five ethically problematic areas: user profiling, data publishing, algorithms design, user interface design and online experimentations, i.e., exposing selected groups of users to specific features before making them available for everybody. Milano et al. [12] conduct an exhaustive literature review of the research on recommender systems and their ethical aspects and identify six areas of ethical concern: ethical content, i.e., content that is or can be filtered according to societal norms; privacy as one of the primary challenges of a recommender system; autonomy and personal identity, opacity, i.e., lack of explaining how the recommendations are generated; fairness, i.e., the ability to not reflect social biases; polarization and social manipulability by insulating users from different viewpoints or specifically promoting one-sided content. Milano et al. [12] also show that the recommender systems are designed with the user in mind, neglecting the interests of the variety of other stakeholders, i.e., interest groups that are being directly or indirectly affected by the recommendation. Polonioli [13] presents an analysis of the most pressing ethical challenges posed by recommender systems in the context of scientific research. He identifies the potential of these systems to isolate and insulate scholars in information bubbles. Also, popularity biases are identified as an ethical challenge potentially leading to a winner-takes-all scenario and reinforcing discrepancies in recognition. Karpati et al. [14] analyse food recommendation systems and identify several ethically questionable practices. They name the commitment to already given preferences and thus to the values of the designers as a contradiction to the potential for ethical content. Privacy, autonomy and personal identity that the authors identify as potentially vulnerable and hence suggest need to be realized via an informed concern and a disclosure about the business model used. Opacity about the origin of the recommendations as well as of the criteria and algorithms used to generate the recommendations. Fairness, polarization and social manipulability as well as robustness of the system complete the list of identified ethical issues for a food recommender.

These approaches discuss ethical impacts of recommender systems from the perspective of the receivers of the recommendations. Milano et al. [12] argue that the social effects such as manipulability and personal autonomy of the user are hard to address, as their definitions are qualitative and require the implementation of the recommender system in the context they operate, while Karpati et al. [14] offer a multi-stakeholder approach to address these issues. The data process-centered approach to analyzing ethical issues suggested by Levina [15] identifies the decision points during the MLS development, while advocating the inclusion of a laboratory phase into the system design to assess the potential consequences (see also [16]).

This research applies a combination of data processing and ethical analysis in the attempt to identify how or whether the identified threads to ethical values that can be realized and mitigated in an MLS design.

IV. Analyzing Ethical Issues within the Data Processing

The general process for analyzing ethical issues within the design of machine learning- based systems has already been roughly outlined in [15]. Here the process is explained in detail and its exemplary application using a scenario of a food recommendation application is presented in Section V.

Fig. 1 shows the stages of data processing according to [17] as well as the aspects that are relevant for discovering potential ethical issues within this specific stage. Although, the *Apply* stage is not an integral part of the data processing pipeline, the effects of the application of the MLS on user behavior are important for its design and are thus included in this analysis. Furthermore, the ethical analysis differentiates between the MLS-user, i.e., a person using the MLS directly within a business process, and an MLS-*affected* user, i.e., a person or a stakeholder that is affected by the results of application of the MLS within a process.

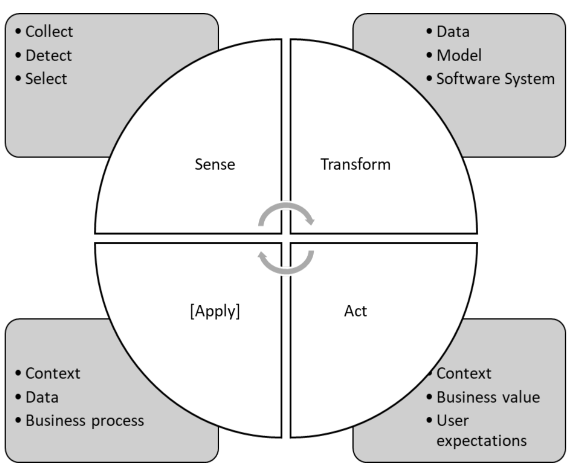

Figure 1. Data processing and relevant aspects for ethical design [18]

In the *Sense* phase the data needs to be collected, pre-processed and stored, i.e., detected for further application. The data features that are relevant to the business problem need to be selected. In the *Transform* phase data analysis methods, i.e., the mathematical model(s) used in the MLS, are in focus. Ethical issues can furthermore arise along the aspects of data manipulation, such as defining the test dataset and its features, as well as the entire software system in which the trained ML model is integrated and that has to be integrated into the business process to provide an added value. In the *Act* phase the integrated MLS in enacted within a business process to provide support for the selected tasks, i.e., to generate business value. To do so, the software system as a whole needs to adhere to the user's expectations towards usability, supported functions and expected output. The *Apply* phase is not included in the data processing pipeline. Nevertheless, to be able to analyze the potential effects of MLS applications, this phase needs to be included to reflect the view of the affected party, i.e., the external party that receives the results of the MLS application at the end of the (business) process.

Hence, this data-centered approach reflects different viewpoints on the data processing and use. While the first two phases, Sense and Transform, focus on the data and their sources, the last two phases are governed by the values of the (business) user and the affected user respectively. Thus, even when the input data for the MLS is machine-generated, the data processing phases require a socio-ethical approach to the requirements analysis and implementation.

In the following subsections the potential aspects that may arise in each phase are presented in more detail and structured along the three sub-categories: ethical aspects, technical aspects and existing methods of risk mitigation for raised technical or ethical questions (see Figures 2-5). While the ethical aspects address value-based issues within the data processing pipeline, technical issues address the technical means and tools that exist and can lead to the raise of ethical issues.

A. *Sense Phase and potential ethical issues*

In the sense phase of the data processing pipeline it needs to be assured that the data have been collected with the informed consent and voluntariness of the data subject. Hence, Fig. 2 shows the sub-division of the phase into the individual categories that can also be extended to accommodate further potential ethical issues.

The ethical value as defined by the European Commission in its ALTAI checklist [9] that is affected the most in the Sense phase, is the value of privacy and data governance. Being an issue that is subject to legislation and public debate, a research direction emerges in the philosophical community calling for empirical investigation of the effects of data collection under the term of ethics of influence [19]. It aims at further investigating of ethical questions in this data processing stage.

Issues associated with data collection have already been addressed in the legal form such as European GDPR legislation. Thus, legal compliance is part of the risk mitigation activities that can be taken by the enterprise applying the MLS. Risk mitigation activities may help to catch ethical issues that occur in the context of appropriation and necessity of data collection. They require, e.g., informed consent of the user to provide interaction or behavioral data. Informed consent also includes the statement of the purpose of data collection implying an opt-in function for data collection. What data is being collected is normally described in the *terms and conditions document of* the MLS. Nevertheless, data-based devices that can contain sensors and processing units might collect more data that the terms and conditions statement declare. These data can be considered a by-product of the service offered, but nevertheless, their collection and potential distribution need to be kept transparent for the future user and affected users.

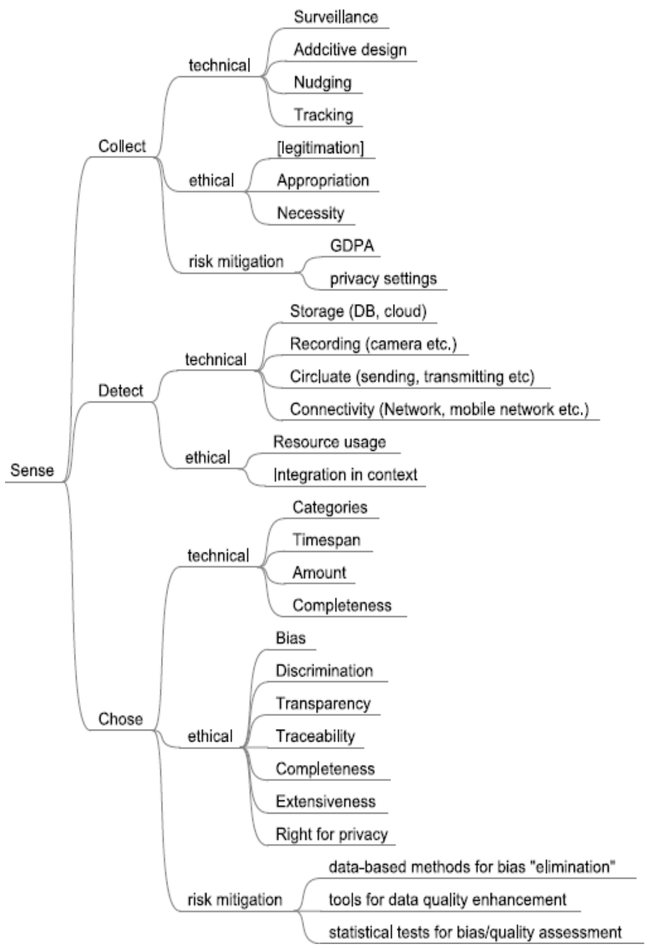

Figure 2. Potential ethical issues in the select stage

The technical realization of the data collection can thus be the origin of ethical issues. Such as the use of dark patterns in system design [20] is attempted at keeping the user engaged with the system are often aimed at collecting more data. The so called smart environments, such as the Internet of Things, are also potential sources for data collection with the focus on specific user behavior [21]. Tracking technologies, such as health tracker or internet cookies, are also technical mechanisms aimed at collecting behavioral data that might exceed the amount of the data required for the original purpose.

B. *Transform Phase and potential ethical issues*

In the Transform phase, technical aspects of model building and training are put into focus, while the ethical values that are most influenced in this phase are the values of transparency of the technical process as well as the societal and environmental well-being as described in the ALTAI checklist [9].

The model construction, i.e., the applied algorithms for pattern recognition, as well as the definition of the thresholds for the MLS results are decision points in the development process that carry potential for ethical issues. Depending on the choice of the algorithms, e.g., the energy efficiency of the performed computation is affected. Using pre-trained models to solve frequently occurring business problems, reduces the resources needed to train the model on the one hand, but on the other hand, this technique has also the potential to lead to homogenous and generalized results [22], i.e., potentially aggravating the ethical issues associated with the value of non-discrimination and fairness. The selection of the computational algorithm is also defined by the expected quality of the results [23]. Hence, the choice is partly made based on the expected quality metrics such as accuracy of the calculates prediction or recommendation by the MLS. Pursuing better accuracy can potentially mean choosing a more resource intensive mathematical model. Hence, this mathematical problem can directly relate to ethical issues.

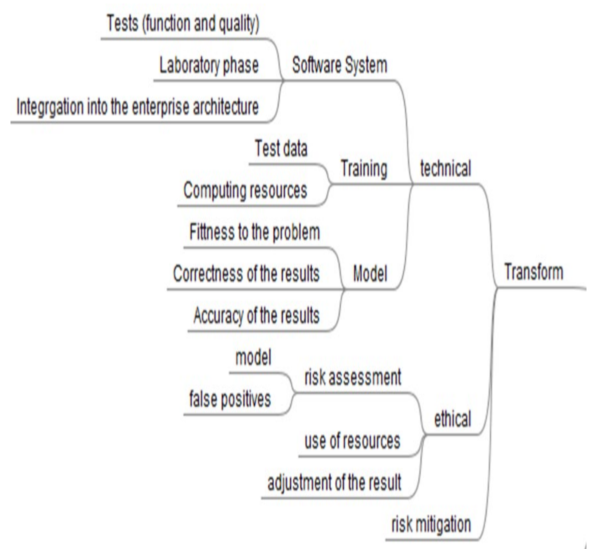

Figure 3. Potential ethical issues in the transform stage

Furthermore, the definition of the thresholds for accuracy or correctness require further ethical decisions [24], e.g., in favor of reduction of false negative or false positive results, depending on the problem at hand. To mitigate these issues, pre-trained models can be used that have already been applied on a similar problem, or industry standards can be addressed. Using industry standards bears nevertheless the negative potential, that the same thresholds would be applied in different use cases, leading to de facto standard values that might in the future lose their semantic correctness. Further potential risk mitigation measures might include meticulous description of the data set used to train the pre-trained model, description of model thresholds and parameters as well as stakeholders involved. Having this description may allow the software developers and model engineers to make an informed decision about the fitness of the model to the problem and data population at hand.

C. *Act Phase and potential ethical issues*

The Act phase focuses on the business process that is supported using the MLS in question. The results generated by the MLS and the usability of the MLS need thus to adhere to the expectations and requirements of its users. Hence, human-computer-interaction and usability aspects as well as the control concepts such as human-in-the-loop are put in focus of the ethical analysis here. Human agency and oversight as well as communication are the values that are mostly affected in this phase. These values should guide the result integration from the social aspect as well as the technical system integration as the technical aspect of the MLS.

The value of human agency and oversight is also addressed by the handling and interpretation of the MLS results for the following process tasks. The information on the meaning of the calculated results in the context at hand as well as their interpretation is crucial for the meaningful application and generation of true added value of the system.

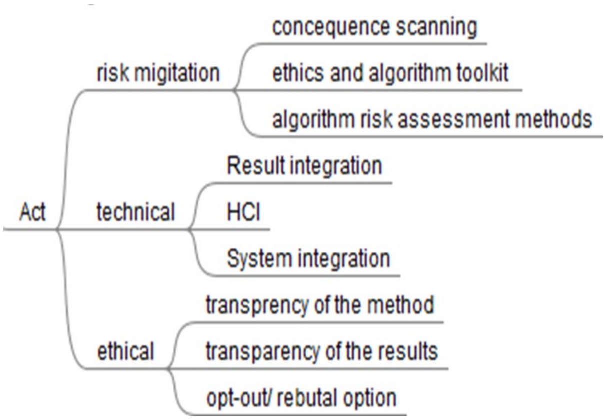

Figure 4. Potential ethical issues in the act stage

Failure to interpret the results might lead, e.g., to false decisions and thus negative consequences for the actors and stakeholders involved in the process. Also occurrence of false positive or negative results, their consequences for the actors involved as well as handling these errors should be included into the business process. Hence, a thorough user training for the process actors involved in the process using MLS is an essential tool for risk mitigation in the act as well as in the apply phase.

D. Apply Phase and potential ethical issues

While the apply phase does not belong to the technical data processing, it is involved in the ethical analysis of handling data in business context. The values accountability, communication and human agency and oversight as described in the ALTAI checklist [9] are mostly affected here, when the MLS application is realized.

The application of MLS in a business process requires good knowledge of the process and of the consequences that should be addressed, e.g., in user trainings. But it may also lead to the loss of previously present skills for the process actors such as moral [25] or decisional [7] de- skilling.

To mitigate these threads to human autonomy, control, expertise, and behavioral change [26] guidelines for MLS development can be applied as well as scheduled audits of the process and the effects on the process performance before and after MLS application can be helpful. Also, changes in the process environment should be monitored using, e.g., performance indicators from the domain of Green BPM [27].

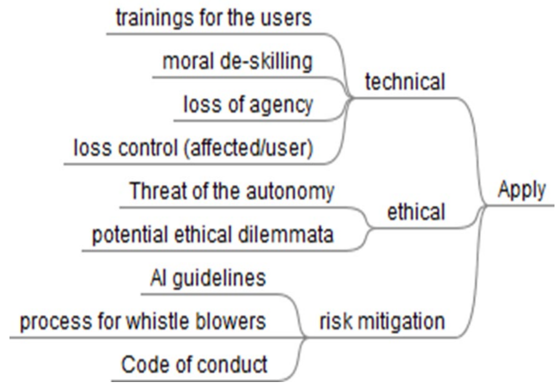

Figure 5. Potential ethical issues in the apply stage

V. AN EXAMPLE APPLICATION: FOODAPP- THE APPLICATION FOR MEAL DELIVERY

The FoodApp is a fictional application based on a three-sided digital platform that is implemented as a mobile app. It is a branch of a fictional large company Acima that offers on-demand individual transportation provided by freelancing drivers. To further explore the transportation market, Acima started FoodApp, a fast growing food delivery platform connecting the customer, restaurant owner and the delivery partner. It allows the customer to choose from a large database of participating restaurants and order a menu to be delivered to the customer’s address via delivery partners. The eater can choose a specific delivery partner based on the ratings of the currently available partners. The payment process is integrated into the platform as is the real-time tracing of the order delivery.

The platform business goal is the “fast and easy food delivery whenever, wherever”. To achieve this goal a MLS, a recommender system, is used to provide the best food suggestions for the user in accordance to the indicated preferences and the order history. The business performance indicators for the FoodApp include the return and re-order customer rates, as well as customer number growth rates. The implemented ML-model is thus optimized to drive user’s re-ordering on the platform.

To use the FoodApp the customer downloads it on the mobile device granting permissions for it to access the location of the device. Further, a profile including information on delivery address, name, e-mail and phone number is required. Payment methods and login to the payment provider is further required. No manual modifications concerning the data collection by the app is possible. Then, the meal preferences such as preferred cuisine or menu item need to be indicated or a meal can be chosen from the provided suggestions. The first suggestions are based on the historical frequency of the orders made within the community in the area of eater’s location. A rating system for restaurant and delivery partner performance is implemented.

The platform gains revenues from the customer via convenience charge, fixed commissions and marketing feeds from the restaurants, while providing the assignments and the payment to the delivery partners, as well as the technical infrastructure for the platform participants. The application is a key driver of Acima's revenue and is a fast- growing meal delivery service with over 15 million users worldwide. Additionally, the platform includes an app for delivery partners that provides the possibility to accept or decline a specific delivery job, monitor the revenues, rate the restaurant's delivery process, as well as provide directions to the restaurant and to the eater.

VI. IDENTIFYING ETHICAL ISSUES USING THE ACENARIO-BASED APPROACH

To identify ethical issues in the MLS used by FoodApp, data process-oriented analysis [15] has been conducted. Since the core component of the FoodApp MLS converts (user) data into a food recommendation, ethical issues are explored using the data-centered ethical analysis approach described in Section IV. The ethical analysis looks at the data process within the system's design and identifies some of the relevant aspects, where ethical values are affected and ethical questions arise influencing the system design. To identify potential ethical issues, questions along the data-processing stages are asked, as suggested by [15].

First potential questions for the first stage, *sense*, are structured along the sub-stages: collect, detect and select. For the act of collection, some of the central questions are:

- Was the user aware of the mode or amount or content or context of data collection?
- Was the data collection conducted with sufficient legal compliance?
- Were any dark patterns [20] involved in the obtainment of the data?
- Are the data collected necessary for the MLS to function according to its purpose?
- Are there opt-in possibilities for different types of data collection?

FoodApp's business goal is to engage the user in the re-ordering of the food via FoodApps's digital platform. The user interacts with the app aiming for a comfortable provision of the favorite food in an efficient way. Therefore, as described in Section I, the user is inclined to give up some autonomy within this process. Nevertheless, in the digital realm the user is often not aware of what elements of his/her *autonomy* are jeopardized when the digital service, here food selection and ordering via a digital platform, is created [12][13]. E.g., in the FoodApp the location information of the device is transferred per default to the platform. Also the app has default access to the microphone and camera of the device. While the user can still change these settings, s/he is often unaware of the default access requirements of the app or does not know what access is needed for the app to function. Thus, the questions that arise in the collect sub-phase should address the actual data collection and their relation to the function of the service provided by the app. Also the questions on whether the data are stored permanently at the platform or have an expiration date are crucial in the detect sub-phase. In the select sub-phase, the questions about:

- data quality
- data sufficiency
- data sources
- representativeness for the solution of the given problem

will have to be addressed. Since data are the fundament for the further model building, their amount, quality, focus in relation to the problem solution (here: providing a food recommendation) as well as the rightfulness of its collection are essential for a mathematically good model design, representative training dataset as well as a socially-aware information system.

Additionally, the amount and sources of the collected data are mostly defined by the *business model*. As FoodApp would like their users to return to the app, it will need among other factors, very good recommendation results as well as a frictionless ordering process together with a reliable problem handling mechanisms to fulfill basic customer expectations [14]. The business model provides essential guidelines for the sense and transformation phases, including the type of information system that can be used to support the *business goals*. The first requirement, i.e., very good recommendation results in terms of user's preferences, can be realized using a recommendation algorithm based on the collected data from the user as well as from the users with similar preferences or history on the platform [14]. Since the user activity data might provide additional patterns for the recommendation, it also provides a potential reason to keep the user engaged on the app for the longest possible time, which might involve the use of dark patterns in the app design [20].

Beside from the user data, FoodApp database should include data on the restaurants available for ordering and delivery through the platform. Addressing the restaurants is part of the business model and might also be part of the business focus, as restaurants can be included on the platform according to specific *criteria*, e.g., reviews on other platforms, personal preferences, number of years in business, etc. leading to a potential pre-selection of available food choice on the platform. To avoid subjectivity in this dataset, a neutral source for the identification of the restaurants and confirmation of their availability should be considered. Additionally, the delivery network of partners that will pick up food at the restaurants and deliver it to the customer's door need to be established and equipped with the means to be contacted, payed and managed by the platform.

Hence, FoodApp needs to establish an *ecosystem*, similar to a classic supply chain, to be able to fulfill its business goal or even to be able to operate according to its business model. Building up such an ecosystem as well as the potential to manage the orders for delivery, provides Acima as a digital platform with a *specific power* over the delivery partners as well as the restaurants that can have extensional effects on the partners involved in the ecosystem as well as the bigger area of stakeholders. See [30] for the discussion of potential ethical issues emerging from the digital platform as an ecosystem.

FoodApp's user profile provides the information that is, among others, needed for the algorithms in the MLS to derive food recommendations. The user does not have any information about the exact *purpose* of the provided datasets, the *data lifecycle*, nor about who has *access* to the (possibly) un-anonymized profile or historical data and about the *data state timeline*, i.e., when the data are transferred or deleted. These aspects can be categorized as "*transparency* issues", since the user does not have the information about FoodApp's processes s/he might need or would like to have.

The FoodApp is designed in a way that on the home screen the most frequent orders for eater's automatically identified location are presented. The user can filter the suggestions using the provided *filter categories*. These categories, defined by the MLS-engineers and designers, include cuisine and menu item names, as well as the ratings of the accordant restaurants. In future interactions with the FoodApp its home screen offers the meals and food items that are most frequently ordered by the eater or users that were identified to have a similar ordering behavior, thus nudging the eater to order the same or similar kind of food [31].

All these features and filtering categories were created as a part of the data *transform* phase, i.e., the model creation and training phase. The first and most significant question in the beginning of the transformation phase is:

- Is the use of machine learning techniques, especially the resource hungry ones such as the neural networks, essential for the solving of the business problem at hand?

The FoodApp has based its business model on the data-based provision of food recommendations and the forwarding of the recommendations to the restaurants and delivery partners. Thus, being data-based, these business questions would require the use of data analysis tools, although the added value of the neuronal networks for the recommendations depends on the quality of data and the accuracy thresholds defined by the product designers.

The *model quality* is in the center of the ethical inquiry in the transformation phase. The set thresholds define mathematical methods, e.g., neural networks vs., e.g., support vector machines, and thus the resources needed to train the model as well as to generate the recommendation. The transform phase does not only include the training and optimization of the models used for the recommendation, it also considers the inclusion of the ML-models into the information systems context.

While definition of food categories as well as the selection of the included cuisines and restaurants is part of the *sense* phase and especially the *select* sub-phase, questions in the transform phase focus on the mathematical transformation of these selected details. Inclusion of, e.g., nudging techniques is also part of the sense phase and the collect sub-phase, but it is strongly defined by the *business model*. Thus, for the transform phase ethical questions could be among others:

- What categories of the collected data are included in the statistical model?
- What is the category that the model is being optimized for?
- What are the quality criteria for the results derived by the MLS?
- What are the thresholds for the quality criteria?

In the *act phase* of data processing, the MLS is integrated into the business process such as its calculated results are being used to create business value and trigger the following business step. For Acima, the value is created when the food delivery order is completed in the FoodApp. Hence, the ordering process is organized in a way that no extended explications or additional information are given so that the user does not have to choose, decide or react during the interaction process. This design allows a *fast phase-out* between opening the FoodApp and ordering the food. This effect can be expected to contribute to user satisfaction and thus re-visiting the platform for the next order.

The process efficiency offered by the FoodApp is also built on the lack of decision possibilities and a limited items selection that is based on the historic and profile preferences for the user. Additionally, the gained comfort for the user in terms of food selection and delivery has implications on the *ecosystem* of the FoodApp. The restaurant partners will be faced with the increased amount of reviews from the delivery customers, potentially forcing them to concentrate on robust packaging to ensure the sound condition of the meal for delivery. More or more robust packaging means more damage to the *environment* but potentially better ratings from the FoodApp users [32].

Furthermore, the food recommendations based on historic and similar orders might lead to *homogenization* of the food offered and prepared in the participating restaurants, as menu items that are ordered less often might not be prepared by the restaurants anymore, potentially leading to the *decreasing of skills* of the cooking staff. The individual delivery of the food orders requires reliable and efficient delivery partners. Acima relies here on its network of drivers for personal transportation that are also incentivized to transport food orders via reward programs. This efficient and effortless process of ordering food for individual consumption can and does cause significant *environmental damage* in terms of air pollution through traffic and waste [32].

Further effects on the *social environment* can also occur. The eater rates the restaurant on the food quality and the delivery partner on the quality of the delivery. The rating is based on eaters' satisfaction with the end result, whereat the traffic situation and other external effects of the recommendation process are not considered. This relationship pattern causes societal effects that are visible in the traffic situation, environmental damages as well as reduction of labor costs and conditions [34][35]. Furthermore, usage of an MLS is probable to change user's behavior [35]. The questions that can be asked in this scenario to identify potential ethical issues are:

- Is it clear for the user that his/her choice of delivery partner would lead to potential loss of jobs for other delivery partners?
- Is it clear for the user what impact her or his order deliver has on traffic or environmental indicators?
- Is it clear for the user what consequences his or her ratings of the restaurant will have on the restaurant?
- Is it clear for the user what effects his or her order will have on his or her recommendations profile?
- Is it clear for the user what are the basics for the recommendations of food/ cuisine/ delivery partner or restaurant within the application?
- Is it possible for the user to change or manage the filtering categories in the app?
- Is it possible for the user to change the profile?

In the *apply* phase, the effects of the integrated MLS are in focus. Here the consequences of the provided food recommendations based on user's historic behavior could lead to *decisional de-skilling* [7] or in this case potentially *homogeneous* food preferences for the eater. Such an automated decision support can also potentially result in the *de-skilling of the evaluation* abilities [25] for the eater in the given context.

The *apply* phase demands for user training (see Fig. 5) or to a smaller degree an explanation of the mechanisms behind the results of the application. So that the model specifications as well as the usability and settings questions can be addressed. User training is here mostly out of scope, since it needs to be implemented as an inherent feature of the FoodApp and would affect the efficiency of the ordering process.

Rating of the delivery partners results in an increasing number of orders for high ranked drivers and in a reduction of delivery orders for the worse ranked drivers. Hence promoting the reviews into the main factor for job acquisition, and thus income, for the drivers. This type of job market is known as the *gig economy* [36]. It provides income potential for the workers while creating an interdependency between the platform customer and the gig worker. This relation seems to remain unclear for the platform customer and is often debated by the platform owners [18][19]. Consequently, the OECD stated in 2016 that digital platforms need social values to be reflected in the platform governance [39].

VII. Integrating the Ethical Issues into the System Design

Based on the ethical analysis of the previous section, Table 1 provides a synthesis of the identified ethical issues and the hereby affected ethical values as defined by the ALTAI checklist. Also, an example how the identified issue can be integrated into the IT system is provided.

The recommendations are structured along the following levels: business level, User Interface (UI) and system level. While business level addresses the definition of the business model and business goals, the system level considers the systems design, including the design of the algorithms. The UI aspects can be used to balance the business goal, i.e., eater's re-ordering behaviour, and the eater's interaction expectations with the digital platform.

This paradigmatic nature allows an insight into the application of the ethical analysis during the MLS design. A more detailed analysis would be needed to provide specific insights on the algorithm level.

TABLE I. Ethical issues of the FoodApp and suggestions for their implementation

Ethical issues	**Affected value(s)**	**Suggestion for implementation**
No explanation on the data storage	Communication; Data governance	*System/UI*: Include clear and transparent information for the user about the data storage, in e.g., in individual contracts or in general terms and conditions. *System*: Develop a concept for deletion routines if the purpose of the data processing is no longer applicable. Accordant selection of the storage location.
No explanation on the purpose of data collection	Communication, Data governance	*UI*: Provide information, e.g., via mouse hover, about the purpose of the data collected in the field, as concrete as possible *System*: To collect data that are not essential for the provision of the service, provide opt-in options by asking the user directly, e.g., "Would you like to help us to improve our service by providing your automated location data?"
Lack of an opt-out for specific data type collection	Privacy, Accountability	*System/UI*: Privacy friendly default settings, e.g., opt-in function for every data item collected instead of the implementation of the "required" fields.
Lack of the possibility to manually adjust the collected data	Human agency and oversight	*System*: Possibility to add or correct data manually, e.g., to type the address for delivery. Establish a reporting system for customers if they wish to have data corrected.
The fact that stakeholders have access to the collected data by FoodApp	Privacy and Data govvernance, Communication	*Business*: No data exchange between other stakeholders without agreements; user can be asked if s/he wants specific data to be shared for a specific purpose with the specific partner (a reimbursement could be offered) Implement an accordant opt-in or rewarding mechanisms for the user in the settings.

Data life cycle is unclear for the user	*Communication, Accountability*	*System*: Describe the data life-cycle to the user, e.g., on the FAQ page. Integrate an automated deletion routines after the needed data are collected; inform the user about the routine in the FAQs, provide opt-ins for further data collection if needed; implement a reward system for additional data collection.
Data state: Is the data anonymized before the analysis?	Privacy, Accountability	*System*: Make clear in FAQ that data is processed anonymously. If this is fulfilled, the GDPR does not apply for the processing. Implement anonymization process via e.g., distributed data bases. If anonymization is not possible, secure data by pseudonymisation and encryption.
Lack of feedback from stakeholders.	Communication, Human Agency and Oversight	*System/business*: Provide a transparent feedback system from and to every actor in the ecosystem; provide an explanation of the ratings and their effects for the actors on the FAQ. Eliminate one-sided rating mechanisms.
Lack of tracing of (e.g.,societal) changes induced by the app.	Transparency, Accountability, Societal and Environmental well-being	Business: Schedule surveys regularly with eaters, restaurants and delivery partners to assess the changes induced in those ecosystems; perform simulations to define potential changes to the traffic in the delivery area; establish contact to the traffic agency; include actionable changes suggestions, e.g., provide contact to a sustainable packaging producer for the restaurant partners; make these actions transparent on the FAQ.
Optimizing the algorithm for user re-ordering	Privacy and Data Governance, Communication	System/Business: Include other stakeholders such as restaurants, delivery partners and the environmental effects with similar weights into the recommendation algorithm; evaluate the systems on a regular basis. UI: Provide different recommendations foci for the user, e.g., focus on preferences, focus on restaurant convenience, etc.
Lack of a test phase about the effects of app usage on the society	Accountability	*Business*: Include a laboratory phase, where the app is tested by the users and stakeholders with evaluation of the UI, UX, legal and ethical aspects plus relevant simulations on the ecosystem e.g., food and restaurant landscapes before release.
Definition of the parameters for food selection by the engineers	Accountability, Privacy and Data governance, Communication, Transparency	*Business/system*: Include a customer survey on which categories they would like to have; change categories or filters for sorting and extend these cate-gories regularly.
Live roll-out of changes to the MLS, i.e.,online experimentation	Accountability	*Business*: Perform changes roll-out during the laboratory phase and simu-lation; when approved, roll-out for the whole community.
Usage of power resources to train the (modifications to) ML-model recommendations are based on a selection of pre-set parameters	Societal and Environmental well-being	*Business*: Change and train the model as rarely as possible, e.g., once a year. *UI*: Provide information why the recommendation was generated and what impact the change of the parameters (e.g., delivery time) would have on the results; Provide possibilities to have parameters adjusted or included into the list.
Lack of understanding of the rating mechanism	Communication, Transparency, Human agency and oversight	*UI*: Provide an explanation of the rating mechanism containing a relative comparison to other ratings, as well as potential consequences (e.g., in a dialog: "Your rating will decrease the number of suggested orders to this delivery partner by 0.2% per cent").
Tendency of the user to accept the MLS suggestions	Communication, Accountability	*UI*: Include a "surprise me" function, where a product is suggested to the eater that does not adhere to his/her top preferences; add a reminder function: "you have already ordered this meal *n* times this month. Would you like to try Y (second choice) today instead?". System: Perform an assessment on how ML might impact user behaviour and present the results on the website.
Effects on the eco-system of the app are not clear for the user	Societal and Environmental well-being, Communication	*Business*: Make the results of the conducted surveys and traffic analysis accessible to the users on the website. *System*: Carry out an impact assessment on the rights of users and also on those of the stakeholders.
Individual food delivery	Human Agency and Oversight	*System*: Include environmental concerns into the algorithm evaluation; *Business*: Provide rewards for environmentally friendly behaviour of the partners (using e-vehicles, e.g., or using environmentally friendly packaging).

Recommendations presentation to optimize the business goal	*Accountability*, *Transparency*	*UI*: Change the UI to be more intuitive for the user with the goal of finding favourite food selection.

The suggestions provided in Table 1 are centred on mainly two aspects: providing information about every data element collected by the FoodApp, i.e., the facet of transparency, and establishing a reward system for the user in return to providing data to the company, i.e., a reward. The implementation of a reward system would implicitly make the data life-cycle more transparent for the user, as well as provide the user with more autonomy within the engagement with the service. It would also help the user to understand that the data is a resource that is traded and thus has a value.

Identified issues that go beyond the business processes might be subject to the interpretation of the regulation or the business ethics. Furthermore, due to the context of the example, some identified ethical aspects are due to the example being positioned in the platform economy and therefore are not specific for every MLS. Nevertheless, bigger negative effects such as the effects on the environment or the society are part of the social awareness and responsibility that are not (and maybe should not be) regulated, but can be supported by socially acceptable IT artefacts.

Therefore, the term of socially acceptable IT has been introduced in [1] to describe a system that considers and integrates ethical requirements into its design. The added effort but also the value of the implementation of the suggestions of the ethical considerations in Table 1 could lead to socially acceptable IT products and thus a realization of a socio-technical IT systems. To ensure the remaining and homogeneous quality adherence, inter-company assessment mechanisms, i.e., ethical quality audits, could be put in place.

VIII. Conclusion

Here a scenario of a fictional food ordering platform that uses a MLS for item recommendations was used to perform an ethical analysis of an MLS. This scenario was chosen as a realisation of a socio-technical system that incorporates system designers, users and stakeholders affected by the system design and process implementation.

The results showed that users of digital services need to be integrated into the design of a socio-technical system as they may have expectations and values that rely on the ethical awareness of the company and thus need to be implemented into the workflow. The examples of how to address these issues demonstrated that changes in the UI, system design but also in the business model can be realistically made to accommodate these challenges. Hence, designing socially acceptable socio-technical IT systems can be a chance to find a niche on the growing and competitive market of consumer-oriented digital services.

Although, the provided approach needs validation and verification in a rea-life environment, it can already be used by the designers and architects of information systems, business developers considering a data-based business model, as well as ISR scientists as it shows how ethical aspects can be incorporated into the context of IT design.

Therefore, future work will aim at establishing the criteria for the definition of the quality requirements for the social acceptable IT, evaluation of the suggested measures, as well as developing methods for the assessment of the effort of their implementation.

References

[1] O. Levina, “Towards Implementation of Ethical Issues into the Recommender Systems Design,” in *ICCGI 2021, The Sixteenth International Multi-Conference on Computing in the Global Information Technology*, 2021, pp. 6–11, [Online]. Available: http://thinkmind.org/index.php?view=article&articleid=iccgi_2021_1_20_18002.

[2] L. Floridi and M. Taddeo, “What is data ethics?,” *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 374, no. 2083. The Royal Society, Dec. 28, 2016, doi: 10.1098/rsta.2016.0360.

[3] Comission on data ethics: "An assessment of the comission on the data ethics" (in German: Datenethikkommission, “Gutachten der Datenethikkommission,”), https://www.bmi.bund.de/SharedDocs/downloads/DE/publikationen/themen/it-digitalpolitik/gutachten-datenethikkommission.pdf?__blob=publicationFile&v=4 (Accessed, July 12 2021), 2018.

[4] G. Baxter and I. Sommerville, “Socio-technical systems: From design methods to systems engineering,” *Interact. Comput.*, vol. 23, no. 1, pp. 4–17, 2011, doi: 10.1016/j.intcom.2010.07.003.

[5] W. L. Robison, *Ethics Within Engineering: An Introduction*. Bloomsbury Academic, 2016.

[6] V. Dignum, “Responsible Artificial Intelligence: Ethical Thinking by and about AI,” 2019. Accessed: Oct. 07, 2019. [Online]. Available: https://icps.gwu.edu/sites/g/files/zaxdzs1736/f/downloads/Virginia%20Dignum_%20Responsible%20Artificial%20Intelligence%20(1).pdf.

[7] L. Floridi and M. Taddeo, “What is data ethics?,” *Philos. Trans. A. Math. Phys. Eng. Sci.*, vol. 374, no. 2083, 2016, doi: 10.1098/rsta.2016.0360.

[8] Doteveryone, “People, Power and Technology: The 2020 Digital Attitudes Report,” 2020. Accessed: May 13, 2020. [Online]. Available: https://www.doteveryone.org.uk/2020/05/people-power-and-technology-the-2020-digital-attitudes-report/.

[9] European Commission, “Assessment List for Trustworthy Artificial Intelligence (ALTAI) for self-assessment | Shaping Europe’s digital future,” 2020. https://ec.europa.eu/digital-single-market/en/news/assessment-list-trustworthy-artificial-intelligence-altai-self-assessment (accessed Feb. 07, 2021).

[10] D. Paraschakis, “Towards an ethical recommendation framework,” 2017, doi: 10.1109/RCIS.2017.7956539.

[11] D. Paraschakis, “Recommender Systems from an Industrial and Ethical Perspective,” in *10th ACM Conference on*

Recommender Systems - RecSys '16, 2016, pp. 463–466, doi: 10.1145/2959100.2959101.

[12] S. Milano, M. Taddeo, and L. Floridi, "Recommender Systems and their Ethical Challenges," *Minds Mach.*, vol. 2, pp. 187–191, 2019, Accessed: Aug. 29, 2019. [Online]. Available: https://philpapers.org/archive/MILRSA-3.pdf.

[13] A. Polonioli, "The ethics of scientific recommender systems," *Scientometrics*. Springer Science and Business Media B.V., pp. 1–8, Oct. 29, 2020, doi: 10.1007/s11192-020-03766-1.

[14] D. Karpati, A. Najjar, and D. Agustin Ambrossio, "Ethics of Food Recommender Applications," 2020, doi: 10.1145/3375627.3375874.

[15] O. Levina, "A Research Commentary- Integrating Ethical Issues into the Data Process," 2020, [Online]. Available: https://library.gito.de/open-access-pdf/Z3-EMoWI_2020_paper_3.pdf.

[16] A. Coravos, I. Chen, A. Gordhandas, and A. D. Stern, "We should treat algorithms like prescription drugs," *Quartz*, pp. 1–8, Apr. 2019, Accessed: Jan. 08, 2020. [Online]. Available: https://digital.hbs.edu/artificial-intelligence-machine-learning/we-should-treat-algorithms-like-prescription-drugs/.

[17] R. Schutt and C. O'Neil, *Doing Data Science- Straight Talk from the Frontline*. O'Reilly Media, 2013, p. 51.

[18] O. Levina, "AI and ethics in medical research. AI-based research in medicine and its ethical challenges," *gesundhyte.de*, pp. 8–11, 2020.

[19] D. Susser and V. Grimaldi, "Measuring Automated Influence: Between Empirical Evidence and Ethical Values," 2021.

[20] C. M. Gray, Y. Kou, B. Battles, J. Hoggatt, and A. L. Toombs, "The Dark (Patterns) Side of UX Design," *Proc. 2018 CHI Conf. Hum. Factors Comput. Syst.*, 2018, doi: 10.1145/3173574.

[21] G. Baldini, M. Botterman, R. Neisse, and M. Tallacchini, "Ethical Design in the Internet of Things," *Sci. Eng. Ethics*, vol. 24, no. 3, pp. 905–925, Jun. 2018, doi: 10.1007/s11948-016-9754-5.

[22] M. Sullivan, "Tech-industry AI is getting dangerously homogenized, say Stanford experts," *FastCompany*, 2021.

[23] Y. Wang, Y. Ning, I. Liu, and X. X. Zhang, "Food Discovery with Uber Eats: Recommending for the Marketplace | Uber Engineering Blog," *Uber Engineering*, 2018. https://eng.uber.com/uber-eats-recommending-marketplace/ (accessed Mar. 17, 2020).

[24] J. Stray, S. Adler, and D. Hadfield-Menell, "What are you optimizing for? Aligning Recommender Systems with Human Values," 2020, [Online]. Available: https://participatoryml.github.io/papers/2020/42.pdf.

[25] S. Vallor, "Moral Deskilling and Upskilling in a New Machine Age: Reflections on the Ambiguous Future of Character," *Philos. Technol.*, vol. 28, no. 1, pp. 107–124, 2015, doi: 10.1007/s13347-014-0156-9.

[26] X. Zhao, M. Maimaiti, M. Jia, Y. Ru, and S. Zhu, "How we eat determines what we become: opportunities and challenges brought by food delivery industry in a changing world in China," *Artic. Eur. J. Clin. Nutr.*, vol. 72, pp. 1282–1286, 2018, doi: 10.1038/s41430-018-0191-1.

[27] O. Levina and M. Behrend, "Assessing the Environmental Impact: A Case of Business Process Analysis in the Automotive Industry," 2016.

[28] A. Rao, F. Schaub, N. Sadeh, A. Acquisti, and R. Kang, *Expecting the Unexpected: Understanding Mismatched Privacy Expectations Online*. 2016.

[29] M. Hatamian, A. Kitkowska, J. Korunovska, and S. Kirrane, "“It's shocking!": Analysing the impact and reactions to the A3: Android apps behaviour analyser," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, Jul. 2018, vol. 10980 LNCS, pp. 198–215, doi: 10.1007/978-3-319-95729-6_13.

[30] O. Levina, "Digital Platforms and Digital Inequality-An Analysis from Information Ethics Perspective," 2019, Weizenbaum Conference, doi: https://doi.org/10.34669/wi.cp/2.4.

[31] R. Zhou, S. Khemmarat, and L. Gao, "The impact of YouTube recommendation system on video views," in *Proceedings of the ACM SIGCOMM Internet Measurement Conference, IMC*, 2010, pp. 404–410, doi: 10.1145/1879141.1879193.

[32] R. Zhong and C. Zhang, "Food Delivery apps are drowning china in plastic," *New York Times*, pp. 1–8, 2019, Accessed: Apr. 25, 2020. [Online]. Available: https://www.nytimes.com/2019/05/28/technology/china-food-delivery-trash.html.

[33] K. Griesbach, A. Reich, L. Elliott-Negri, and R. Milkman, "Algorithmic Control in Platform Food Delivery Work," *Socius Sociol. Res. a Dyn. World*, vol. 5, p. 237802311987004, Jan. 2019, doi: 10.1177/2378023119870041.

[34] V. Dorner, O. Ivanova, and M. Scholz, "Think twice before you buy! how recommendations affect three-stage purchase decision processes," in *International Conference on Information Systems (ICIS 2013): Reshaping Society Through Information Systems Design*, 2013, vol. 5, pp. 4278–4297.

[35] M. De-Arteaga, R. Fogliato, and A. Chouldechova, "A Case for Humans-in-the-Loop: Decisions in the Presence of Erroneous Algorithmic Scores," *Conf. Hum. Factors Comput. Syst. - Proc.*, Apr. 2020, doi: 10.1145/3313831.3376638.

[36] G. Friedman, "Workers without employers: Shadow corporations and the rise of the gig economy," *Rev. Keynes. Econ.*, vol. 2, no. 2, pp. 171–188, Apr. 2014, doi: 10.4337/roke.2014.02.03.

[37] J. Staufenberg, "Deliveroo courier strike: Employers cannot 'simply opt out of the National Living Wage', says Government," *The Independent*, 2016.

[38] M. Dewhurst, "Deliveroo couriers are right to strike: the company's claims of freedom are a sham," *The Guardian*, 2016. https://www.theguardian.com/commentisfree/2016/aug/16/deliveroo-couriers-strike-freedom-william-shu (accessed May 11, 2020).

[39] OECD, "Protecting Consumers In Peer Platform Markets: Exploring The Issues Background report for Ministerial Panel 3.1," Nov. 2016.