Augmenting machine learning with human insights: The model development for B2B personalization

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ABSTRACT

Purpose _ Machine learning (ML) techniques are increasingly important in enabling business-to-business (B2B) companies to offer personalized services to business customers. On the other hand, humans play a critical role in dealing with uncertain situations and the relationship-building aspects of a B2B business. Most existing studies advocating human-ML augmentation posit the concept without providing a detailed view of augmentation. Therefore, the main purpose of this paper is to investigate how human involvement can practically augment ML capabilities to develop a personalized information system (PIS) for business customers.

Design/methodology/approach _ The authors developed a research framework to create an integrated human-ML PIS for business customers. The PIS was then implemented in the energy sector. Next, the accuracy of the PIS was evaluated using customer feedback. To this end, precision, recall, and F1 evaluation metrics were employed.

Findings _ The computed figures of Precision, Recall, and F1 (respectively 0.73, 0.72, and 0.72) were all above 0.5 thus the accuracy of the PIS was confirmed. Finally, the article presents the research model that illustrates how human involvement can augment ML capabilities in different stages of creating the PIS, including business/market understanding, data understanding, data collection and preparation, model creation and deployment, and evaluation phases.

Originality/value_ This paper offers novel insight into the less-known phenomenon of human–ML augmentation for marketing purposes. Furthermore, the article contributes to the

B2B personalization literature by elaborating on how human experts can augment ML computing power to create a PIS for business customers.

1. Introduction

Given the importance of maintaining long-term relationships with business customers in industrial markets, the usage of the personalized information system (PIS) can positively influence the development of business-to-business (B2B) relationships (Saura et al., 2020). A PIS is a system that conveys messages or information tailored to a user's or a user group's interests, preferences, needs, and context (Khosrow-Pour, 2008, p. 3063). A PIS can enhance the relational ties in B2B relationships by increasing the number of contacts (Murphy and Sashi, 2018). Furthermore, evidence has shown that a PIS can improve the effectiveness of B2B customer communication by offering more personal and relevant content (Mero et al., 2022). A PIS typically relies on human-made automation rules (Järvinen and Taiminen, 2016; Mero et al., 2022). However, embedding a machine learning (ML)-based recommendation approach in a PIS could empower marketers to tackle the problem of information overload (Sun et al., 2019) and help B2B executives acquire useful information from the increasing amounts of data they receive (Haji Habibi et al., 2015).

Unlike traditional methods such as interviews, surveys, or observations which are commonly used to investigate and identify customer needs and expectations (Edvardsson et al. 2012), ML techniques are able to automatically detect patterns in the dataset, learn from mistakes, and self-correct (Kühl et al., 2022). Using various algorithms, ML techniques (i.e., supervised, unsupervised, and reinforcement) help firms generate predictions needed to make decisions (Hagen et al., 2020). In addition, ML features including automation, pattern detection, and prediction generation could result in a considerable reduction in the required cost and time compared to traditional methods (Collingwood and Wilkerson, 2012).

Over recent years, advances in ML techniques have provided innovative possibilities to assist marketers in offering personalized marketing services (Jain et al., 2021; Liu, 2020) that have been increasingly requested by B2B customers (Kessinger, 2022). Furthermore, previous studies have confirmed other useful outcomes of artificial intelligence (AI) and ML adoption in the B2B sector including accuracy improvement, better decision-making, enhanced customer relationships, sales increase, cost reduction, efficiency improvement, and risk reduction (Chen et al., 2022). Nonetheless, based on a recent survey study, 63% of B2B marketing managers still have problems in their personalization efforts, yet only 17% use AI and ML across the function (Gartner, 2021). A question arises here: Why are many B2B companies still reluctant to leverage ML in order to offer personalized marketing services to their customers?

In fact, despite the efforts of B2B firms to assimilate AI and ML techniques to provide superior personalized services and attain competitive advantage (Papagiannidis et al., 2023), due to challenges such as lack of theoretical background (Ma and Sun, 2020), privacy concerns, and ethical dilemmas like AI fairness (Wirtz et al., 2020), many firms and their employees continue to confront the dilemmas of adopting AI and ML (Papagiannidis et al., 2023). Some scholars believe AI and ML techniques will be more efficient if the computing power of ML and human insights are connected using integrated models (Davenport et al., 2020; Jarrahi, 2018; Kaplan and Haenlein, 2020; Ma and Sun, 2020). However, it appears that due to the ambiguity of deploying ML techniques combined with human insights (Graef et al., 2020; Teodorescu et al., 2021), further research is needed to explore the practical details of achieving human-ML augmentation for different purposes (Davenport et al., 2020; Kaplan and Haenlein, 2020; Ma and Sun, 2020); especially in B2B contexts, where the research on digital technologies and AI is fragmented and divergent (Zhai et al., 2023), and the gap between practice and academic research is felt (Cortez and Johnston, 2017). Therefore, the primary goal of this article is to enhance B2B scholars' and practitioners' understanding of the theoretical and practical details of human-ML augmentation to create a PIS. To reach this goal, the article focuses on answering the question of *how human involvement can practically augment ML computing power to create an efficient PIS for business customers?*

This article's contributions are threefold. First, much of the existing literature advocating augmentation posits the concept without providing nuances of human-ML augmentation (Teodorescu et al., 2021); so, this study aims to provide more detailed theoretical aspects of human-ML augmentation with a focus on the B2B context. Second, although many firms recognize the potential of augmenting human insights with intelligent systems, few have accomplished such aspirations at scale (Barro and Davenport, 2019; Teodorescu et al., 2021). The main reason for this failure is the ambiguity of using ML techniques combined with human insights (Graef et al., 2020). This article thus explains this process in more detail by presenting a model that illustrates the main stages of human-ML augmentation for B2B personalization. Third, given the fact that B2B marketing research will become more relevant for firms and business theory if practice and academic studies are brought together (Cortez and Johnston, 2017), this article provides empirical research with which to practically develop and examine the PIS for business customers.

Accordingly, the remainder of this paper proceeds as follows. The next section highlights prior findings on the theoretical and practical contributions of humans to augment ML capabilities. The third section presents the research framework. The fourth section explains the research methods. The fifth section is devoted to explaining the details of conducted empirical research. The sixth section elaborates on the research findings and presents the research model. In the final section, we discuss the research implications and suggest directions for future research.

2. Framework development

Integrated human-ML models should enable the creation of collaborative intelligence through which humans and AI actively and continuously enhance each other's complementary strengths (Wilson and Daugherty, 2018). Hence, such collaborations may empower firms to shift their businesses' traditional boundaries (Ansari et al., 2018). In this vein, the main concentration of this article is on identifying different human contributions that can augment ML computing power, especially for B2B personalization. Thus, the rest of this section is devoted to elaborating on the findings of previous studies on how human involvement can augment ML capabilities.

First, despite the considerable potential of ML in analyzing customers' needs and personalization through interpreting numeric and non-numeric data (Chui et al., 2018), a key challenge is to build a transparent model structure and clear links between variables as they often lack the theoretical basis (Ma and Sun, 2020). Thus, one of the foremost contributions of humans to ML techniques is using human insights in order to develop a robust theoretical backbone and increase the interpretability of outputs.

Second, human tactic knowledge could augment ML computing power in selecting appropriate features (Cheng et al., 2006; Izadi et al., 2013), as well as suitable algorithms, which are serious challenges when applying ML techniques (Lieder et al., 2014). Previous research in decision-making has increasingly stressed the importance of considering the context in which the problem is embedded (Fantino and Stolarz-Fantino, 2005; Zerilli et al., 2019). Years of experience in performing qualitative assessments in various situations often help human decision-makers make choices, considering the actual context of the problem. In other words, human involvement (e.g., B2B experts) often enables the selection of appropriate solutions or methods, considering the unique context in which the problem has arisen.

Third, to materialize the synergistic relationship between ML and humans, one can combine superior human intuitive judgment with the speed of ML techniques in collecting and analyzing information (Jarrahi, 2018; Teodorescu et al., 2021). This augmentation could specifically assist B2B firms in collecting data, because data for B2B marketing are typically rare, and their value is difficult to extract (Lilien, 2016). Thus, B2B firms often need to employ more innovative ways to collect and process data than methods commonly used in business-to-consumer (B2C) environments. To this end, human judgment could specifically help ascertain which variables or future events (out of endless factors) can be used for data collection (Jarrahi, 2018). This approach would especially benefit firms that do not have an organized database of customers.

Fourth, in addition to humans' contributions to augmenting ML during the initial phases of ML application (e.g., choosing appropriate theories, features, and algorithms), human involvement can also enable firms to assess customer feedback through direct contact, ensuring their satisfaction with ML-based systems' outputs. This human involvement particularly helps B2B firms to apply account-based marketing that allows B2B marketers to communicate with individual prospects or accounts (i.e., strategic customers) to create a superior personalized experience for them (Golec et al., 2019). Furthermore, given scholars' and practitioners' concerns about the dark side of AI that cause unfair or biased results (Wang et al., 2020; Akter et al., 2021), human involvement can specifically prevent the ethical and moral implications of ML bias by assessing customer feedback (Sun et al., 2020). For example, many recent cases have shown that gendered, racial, and socio-economic biases emanate from AI and ML applications (Hunter, 2020; Akter et al., 2021). However, recent studies' results have proven that continuous feedback improves an AI model, and practical responses to such insights reduce algorithm bias (Akter et al., 2021). Hence, the human contribution to gaining and evaluating customer feedback can ensure that firms' automated technology is enacted fairly and does not discriminate against any group of people (Teodorescu et al., 2021).

Based on the above arguments, the remainder of the current section discusses humans' role in augmenting ML techniques to create a PIS by (a) establishing a theoretical framework, (b) selecting an appropriate ML technique, (c) applying tactic knowledge-driven feature selection, and (d) evaluating customer feedback to improve the model's outputs and reduce ML bias.

2.1. Establishing a theoretical underpinning

Given the importance of an in-depth understanding of the informational needs of B2B audiences for creating an efficient PIS, in this section, we aim to develop a theoretical basis for identifying business customers' interest in different types of content. Indeed, employing an appropriate theory that considers audiences' needs and motivations for consuming information enables firms to publish a range of relevant and compelling content that may help enhance customers' engagement and develop relationships with customers (Yaghtin et al., 2020; Yaghtin et al., 2022).

In this research, we adopted the uses and gratifications (U&G) theory that was initially proposed by Katz (1973) and suggested a range of audiences' informational, motivational, and emotional needs for obtaining information. The U&G approach establishes a value-based perspective on providing content for customers (Bruhn et al., 2014), given that people consume content in order to satisfy specific needs (Katz, 1973; Yaghtin et al., 2022). Despite disparities between B2B and B2C contexts (Christopher and Marder, 2017), U&G theory has been examined in both the B2C and B2B literature (Bruhn et al., 2014; Christopher and Marder 2017; Grissa, 2017). U&G needs consist of five main categories: cognitive, affective, social integrative, personal integrative, and tension release motivations (Katz et al., 1973). To acquire more in-depth insight into the types of appealing and valuable content for business audiences, we conducted a literature review. The initial sample of possibly relevant publications, including 39 studies, were preliminary screened based on general exclusion criteria such as time frame (published academic studies between 2011 to 2021) and language (English), as well as their overall relevance to the topic (compelling content types for audiences). Then, selection criteria limited the selected studies to 21 contributions that were focused on B2B marketing and could help identify valuable content types for business customers. At this stage, all studies were assessed based on the full-text review. We then categorized the content types based on U&G theory (see Table 1).

Table 1

Based on our findings shown in Table 1, within the B2B space, the underlying drivers of content consumption are more utilitarian (Christopher and Marder, 2017) when business customers use information that mainly aligns with their business purposes. However, emotional gratification, personal motives, and the social components of communication still play a significant role in relation to customer perceptions, setting expectations, and improving coordination with B2B customers (Murphy and Sashi, 2018; Bruhn et al., 2014).

2.2. Selecting an appropriate recommendation method

Recommendation systems use personalized information-filtering technology to provide intelligent recommendations about products, services, or information that are more likely to suit customer preferences (Chen and Liu, 2017). To this end, PISs apply two broad recommendation approaches: collaborative filtering recommendation and content-based recommendation (Abbasi et al., 2019). Another common approach is the hybrid recommendation, which involves a combination of more than one model (Logesh and Subramaniyaswam, 2019).

The collaborative filtering recommendation technique is the most mature, as well as the most commonly implemented (Isinkaye et al., 2015). Collaborative filtering systems make predictions about customers' or users' interests based on data collected from other customers or users who have demonstrated similar patterns (Deng et al., 2020). A content-based recommender system analyzes the description of products or different items and/or sets of items that were previously rated by a customer and then constructs a model or profile of customer preferences that is based on the object's feature rated by the customer (Sattar et al., 2017). Collaborative filtering has some major advantages over content-based filtering techniques in that it can be used in domains where there is not much content associated with items and where content is difficult for a computer system to analyze (Isinkaye et al., 2015). Moreover, deploying a collaborative approach requires less effort from respondents to answer questions, because the users of the collaborative filtering system do not need to answer a list of questions, which is often required for using content-based recommender systems (Wang et al., 2014). Nevertheless, this technique suffers from the cold start problem (Tahmasebi et al., 2021), meaning that the effectiveness of the collaborative filtering technique decreases in the recommendation of unknown items (Ziarani and Ravanmehr, 2021).

To select an appropriate recommendation technique for developing an ML-based PIS, the advantages, and disadvantages of recommendation techniques and algorithms should be carefully examined. To this end, it is necessary to include domain expertise or knowledge of the essential aspects of a specific field of inquiry. This is because human expertise can help enormously in selecting a suitable technique using domain knowledge by considering the actual context of the problem.

2.3. Choosing suitable features

In ML-based systems (e.g., an ML-based PIS), the quality of the outputs refers to the fitness of features that are selected for the specific purpose of the analysis (Lee and Shin, 2020). Feature selection is defined as the application of effective methods to reduce feature space in order to pinpoint only the most suitable features (Di Mauro et al., 2021). Feature selection techniques help eliminate irrelevant and redundant features to reduce the computational cost of modeling (Brownlee, 2019) and improve the ML performance (Sheikhpour, et al., 2017). There are two commonly used feature selection approaches: automatic feature selection techniques (i.e., the data-driven approach) and expert judgment (i.e., the tactic knowledge-driven approach) (Cheng et al., 2006).

It should be noted that most data-driven techniques ignore legal and ethical requirements of justifiable feature selection (Zacharias et al., 2022). In this sense, using tactic knowledge-driven methods can help meet legal and ethical requirements of choosing features to solve a business problem. Another problem with using data-driven techniques for B2B marketing purposes is that many B2B firms do not have access to sufficient or organized datasets of customers (Lilien, 2016) which is the minimum requirement for deploying automatic feature selection techniques. For example, B2B data may exist in many different databases and systems (e.g., transactional databases, several SaaS tools, and CRM systems) that often do not connect to each other (Smallcombe, 2022). Consequently, sometimes organizations need to collect and organize data from scratch. In such cases, using tactic knowledge enables firms to ascertain what variables or future events can be used for data collection (Jarrahi, 2018). This approach would particularly help B2B firms to create new organized databases based on the specific requirements of the firm.

It should also be considered that relevant features may be different depending on the business context and the nature of the problem (Brown, 2019). One can argue that such nuances in selecting relevant features can only be identified using expert judgment; however, given the advantages and disadvantages of data-driven and tactic knowledge-driven approaches, these methods can augment each other to select the most relevant features. Hence, using a two-step feature selection approach consisting of the tactic knowledge-based perspective and the data-based feature selection approach (using the ML-based method) might enhance the accuracy of an ML model.

2.4. Evaluating customer feedback

With the widespread use of ML-based systems in our everyday lives, accounting for fairness has gained importance in the implementation of these techniques (Mehrabi et al., 2021). However, the essential fairness conditions for applying ML algorithms come with the specific problem that it is impossible to be absolutely fair across various groups (Kleinberg et al., 2016). First, an ML-based PIS is a data-driven system that requires data upon which to be trained. Therefore, data are tightly coupled to the functionality of the ML-based PIS. Accordingly, where the underlying training data contain biases, the ML algorithms are trained on biases and reflect them in their predictions (Mehrabi et al., 2021). Hence, one can hardly find a flawless system operating with ML, especially considering the real-world conditions with correspondingly chaotic and hard-to-clean datasets (Hagendorf, 2019). Furthermore, even if the data are not biased, ML algorithms may display biased behavior due to certain design choices. Then, the outcomes of these biased algorithms can be fed into real-world systems, resulting in more biased data for training future algorithms (Mehrabi et al., 2021).

Moreover, what is perceived as fair or unfair may depend on the specific objectives that a system is designed for (e.g., individualistic or organizational goals); thus, the judgment in the case of the intensity of the ML bias could be remarkably context-dependent. In this regard, incorporating human insights can greatly help evaluate customer feedback to ensure that ML techniques are enacted fairly (Teodorescu et al., 2021). Indeed, continuous feedback and practical responses to such insights can improve an AI model and reduce algorithm bias (Akter et al., 2021).

3. Research Framework

To deploy human-ML models—or, more generally, human–AI models—a common approach that firms have applied is using AI to lay the initial groundwork and then employing human expertise to finish the work (Vijayan, 2019). This approach has mainly been based on the logic that using AI to achieve very highly accurate data analysis can often be costly (Ng et al., 2020); thereby, in order to decrease the expenditures of using AI in the whole process, human experts are employed in some parts of the process. However, the need for leveraging more advanced human-ML models that allow firms to exploit opportunities created by collaborations between human insights and ML computing power is still felt. Especially, in the B2B context, wherein different aspects and use cases of human-ML augmentation remain largely unknown (Teodorescu et al., 2021). Furthermore, the use of integrated human-ML models can enable B2B firms to conduct nascent B2B marketing strategies, such as the account-based marketing program that heavily relies on highly qualified personalization techniques (Burgess and Munn, 2021; Golec et al., 2019), thus helping them identify specific customer needs as well as strengthen relationships with business customers.

Some standard data mining models, such as the Cross-Industry Standard Process for Data Mining (CRISP-DM), describe common approaches used by data mining experts (Shearer, 2000). However, these models mainly concentrate on implementing a data science process (Hotz, 2022) without focusing on human-ML integration during the process. Given the key stages of CRISP-DM including business/market understanding, data understanding, data preparation, model creation and deployment, and model evaluation, and in light of prior discussions made in this paper, we developed an integrated framework that illustrates how human involvement can augment ML to create a PIS for B2B firms (see Figure 1).

i) first, the framework proposes the use of human knowledge (i.e., B2B marketing experts) to establish a theoretical underpinning (i.e., employing the U&G theory to establish a theoretical basis for creating a PIS for business customers). The use of an appropriate theory can help understand the business problem in view of the market context. Further, incorporating a relevant theory (e.g., the U&G theory) in the model enables the usage of relevant hypotheses and identification of the main variables that can impact the results, thus facilitating the interpretation of the model outputs; ii) in the next stage, the framework suggests applying domain expertise to select suitable ML techniques considering advantages and disadvantages of different ML techniques for a particular domain; iii) the framework suggests the use of the tactic knowledge of B2B experts to choose the most relevant features in order to augment the data-based feature selection techniques; iv) in addition to data understanding, human involvement can also facilitate the data collection phase which especially helps B2B firms to establish organized datasets; v) the recommendation model is created by employing a reliable dataset (Isinkaye et al., 2015). At this stage, the ML-based PIS can rely on different types of input, depending on the recommendation approach (i.e., collaborative filtering recommendation and content-based recommendation). For example, the system can use the most convenient high-quality explicit feedback which includes explicit input from business customers regarding their interest in various content types, or implicit input from other customers, users, or respondents who have demonstrated similar patterns (Deng et al., 2020); vi) the recommender model computes the similarities considering the customers' features or item features evaluated by customers in the past; vii) After computing similarities, the PIS is able to propose appropriate content for each business customer; viii) the framework proposes that the customers' feedback with high satisfaction scores be directly submitted to the customer data; ix) in terms of the customers' feedback with low satisfaction scores, the research framework suggests employing marketing experts to evaluate the customers' feedback considering the theoretical basis of the model (i.e., U&G theory). As a complementary option, marketing experts can also make direct contact with customers to identify their exact content preferences. This direct feedback is added to the customer database to train the model. Human involvement in this stage helps reduce ML biases and inaccurate outcomes and thus can complement the ML training phase to improve the PIS's future recommendations.

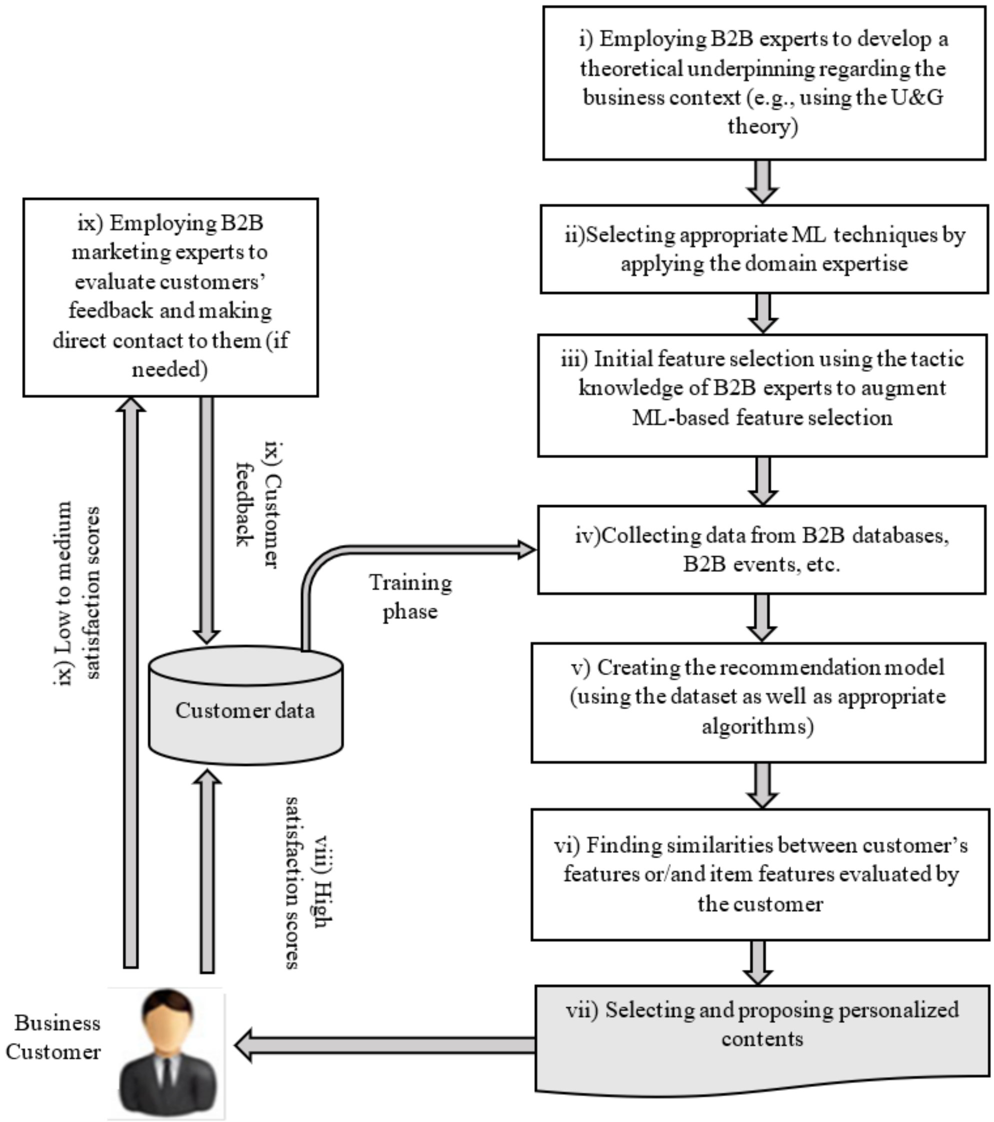

Figure 1. The proposed integrated human-ML framework for creating a PIS for business customers

4. Methods

In this study, we conducted empirical research to create and examine an integrated human-ML model-based PIS in a real-world context and within the energy sector. Data mining models and methodologies such as CRISP-DM and SEMMA provide a holistic view of the data mining process (Huber et al., 2019); hence, they have been applied and used by many practitioners and scholars to conduct data mining process and business research (e.g., Esmaieeli Sikaroudi et al., 2015; Vazan, 2019; Ayele, 2020). While standard data mining models take a data-driven approach to implementing data mining projects, they may disregard the role of human abilities and insights in augmenting data processes to improve the efficiency of the final model (Ma and Sun, 2020). Therefore, some researchers have proposed the usage of mixed human-data-driven approaches (e.g., Schäfer et al., 2018; Davenport et al., 2020; Kaplan and Haenlein, 2020; Ma and Sun, 2020), and some scholars applied hybrid human-data-driven models in their research. For instance, Karlinsky-Shichor and Netzer (2023) proposed a human-machine hybrid approach to automating decision-making in high-human interaction environments in the B2B retail context. Also, Schäfer et al. (2018) synthesized quality management tools with the CRISP-DM methodology in a data mining project for the development of an error forecasting system. Similarly, this article suggests developing an integrated human-ML model to create a PIS model for business customers.

Considering the phases of standard data mining approaches (e.g., CRISP-DM and SEMMA) and regarding the identified stages of our research framework, we propose conducting the following phases to create an integrated human-ML model of PIS for business customers: 1) the pre model-creation phase: in this phase i) the U&G theory is used to identify and create appropriate contents, ii) the tactic knowledge of human experts is employed to select a suitable ML technique, iii) the initial feature selection is conducted using the fuzzy Delphi method with the participation of B2B experts; 2) data collection and preparation phase: the required data are collected from relevant industrial events using the structured interviews; 3) model creation and implementation phase: the ML model is developed using the collected data and the Python programming language; 4) the model evaluation and improvement phase: the model is implemented then evaluated. To this end, the customers' feedback is evaluated using precision, recall, and F1 evaluation metrics, as well as human judgment and expertise.

The next section is devoted to elaborating on the details of our empirical research.

5. Empirical research

5.1. The pre model-creation phase

5.1.1. Creating content using the U&G theory

Our primary reason for selecting the energy industry was the importance of preparing B2B audiences for a remarkable transition in the energy sector because energy companies must reinvent themselves to scale access to clean and sustainable energy (Ali, 2019). In this context, disseminating relevant and valuable content might play a significant role in facilitating this transition. In light of our findings from the conducted literature review (Table 1) and drawing on the U&G approach, we identified nine content types associated with the five main categories of U&G theory that might be valuable and appealing to business audiences. The relevant contents are then created based on the identified content types according to the U&G theory and the specific objectives of the firms (see Figure 2).

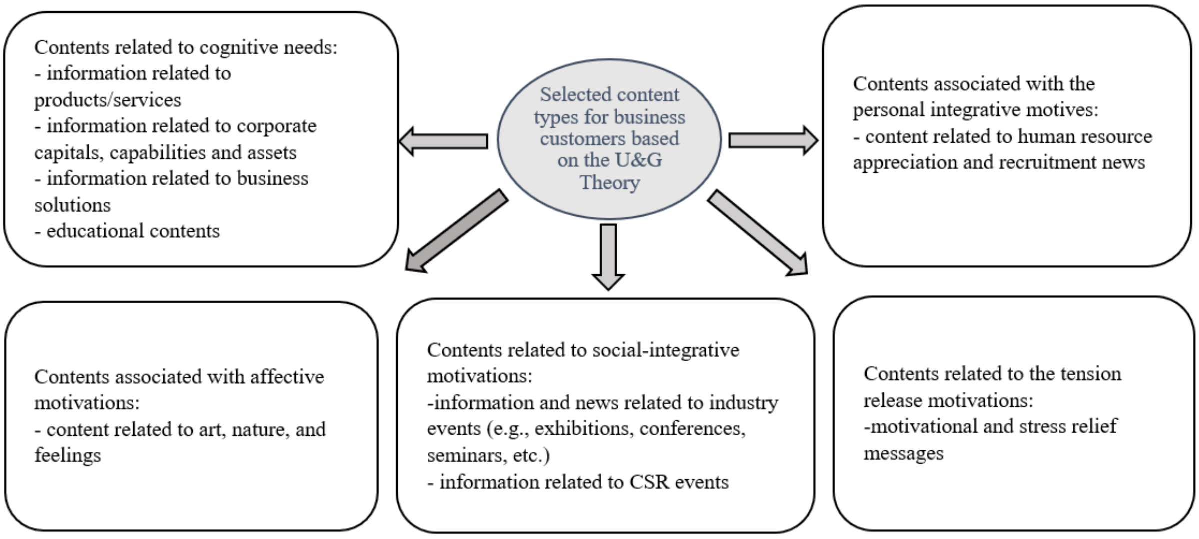

Figure. 2. The informational needs of business audiences based on U&G theory

5.1.2. Choosing an appropriate ML-based recommendation method

In this research, we applied the model-based collaborative recommendation technique to create the PIS. Our main reason for not using the content-based approach is the preliminary requirement of this method for having in-depth knowledge of item features that were evaluated by customers in the past. Instead, the collaborative approach can be used in domains where there is not much information associated with items. Since in this study, no previous evaluation has been conducted in terms of the B2B customers' interest in different types of content, therefore, we use the decision tree-based collaborative recommendation technique that can quickly recommend items without any requirement for using item features evaluated by the customer him/herself. Using the decision tree algorithm, the joined dataset, including the data related to the B2B respondents and the data related to different content types, can act as the training data for detecting similarities. As a result, with the item profile and rating matrix, the system will be able to classify customer interest in different content types.

5.1.3. Initial feature selection for collecting data

Since in ML models, the quality of outputs refers to the fitness of selected features for the specific purpose of analysis (Lee and Shin, 2020), it is essential to find out which features are best suited for the specific purpose of the research. When there is insufficient data for employing ML-based feature selection techniques, Izadi et al., (2013) propose the usage of the fuzzy Delphi method to select the required features.

In this research, we use a two-step feature selection method. To this end, first, we employ the tactic knowledge of human experts using fuzzy Delphi to select initial features. In fact, the fuzzy Delphi method helps us determine appropriate features that are required to collect data from B2B respondents. Then, we use the ML-based feature selection technique to select the most suitable features which leads to improving the predictive power of the model (Cheng et al., 2006).

Accordingly, we initially selected features that are more specialized for predicting the informational needs of business customers, such as job position, job discipline, and work experience as well as traditional features, including age, gender, education, income, region, nationality, and favorite hobbies. Next, we employed the fuzzy Delphi technique to derive insight from domain experts to select the most suitable features (Izadi et al., 2013). Then, we used the selected features to conduct the data collection phase. After collecting the data, we applied LASSO logistic regression as an automatic feature selection mechanism to enhance the accuracy of the PIS model.

To carry out the Delphi method, 15 experts from different departments of an energy company were selected. The panel consisted of experts from sales and marketing (four experts), human resources (three experts), information technology (two experts), public relations (two experts), engineering (two experts), and management (two experts) departments. The experts' opinions about the significance of initial features for predicting the informational needs of customers were rated on a five-point Likert scale. We used the linguistic variable scale and its equivalent triangular numbers in order to transfer the experts' opinions to the triangular membership function (see Table 2).

Table 2

In addition, to rank the variables, the average of the experts' opinions was calculated with the Minkowski formula (1):

$$\chi = m + \frac{\beta - \alpha}{4} \ . \qquad (1)$$

Table 3 illustrates the mean value of expert opinions, as well as the results of the Delphi method in terms of the selected features. Based on the results, the most suitable features include age, gender, education, region, favorite hobbies, and job discipline.

Table 3

The next section is devoted to explaining how we conducted the field study to create and test the PIS.

5.2. Data collection and preparation phase

In order to create an ML model, large volumes of data should be analyzed for the learning process (Gregory et al., 2020). As discussed in the previous sections, organized data in B2B environments are often rare. Industrial events (e.g., exhibitions, conferences, and trade shows), wherein hundreds of experts and professionals in a particular field gather during a limited time, are a suitable opportunity for data collection. In this research, the required data were collected from visitors of three international exhibitions held from August 2019 to May 2021 in the Middle East. The collected data from 1155 B2B visitors were collected in order to compute the similarities of "like-minded" customers, which is necessary for applying the collaborative recommendation technique. We designed structured interviews and asked questions from respondents (i.e., 1155 visitors) from 42 countries. To develop the PIS, the model needs the input data (X), including data related to the age, gender, education, region, job discipline, and favorite hobbies of each industrial visitor (i.e., the selected features in section 5.1.3). Furthermore, to provide the outputs (Y), we asked the respondents to select their three first preferred content types from the pre-defined content types (see Figure 2). This would enable the PIS to predict three preferred content types for each business customer. The U&G-based content classes were not unveiled to the respondents; thus, they had no obligation to choose content types from different U&G categories. Table 4 presents the percentage distribution of respondents by age, gender, education, region, job discipline, and their favorite hobbies.

Table 4

Before we analyzed the data, we prepared them. Data preparation, consisting of data organizing and cleansing phases, is usually a time-consuming process; however, structured interviews facilitated the creation of a structured database in our research. Consequently, the whole data preparation process was conducted in less than five days, from 12 May 2021 to 17 May 2021.

5.3. Model creation and implementation phase

In this study, we used Python programming language, which offers strong performance and versatility in conducting empirical marketing research (Villarroel Ordenes and Silipo, 2021). The codes were written in such a way that the model could predict the three first preferred content types of the prospect/customer just by having required data about six characteristics (i.e., age, gender, education level, region, favorite hobby, and job discipline). Figure 3 indicates the outputs of the PIS in predicting the three first preferred content types for two hypothetical samples. As illustrated in Figure 3, with information about the six customer attributes, the model is able to predict a customer's preferred content types.

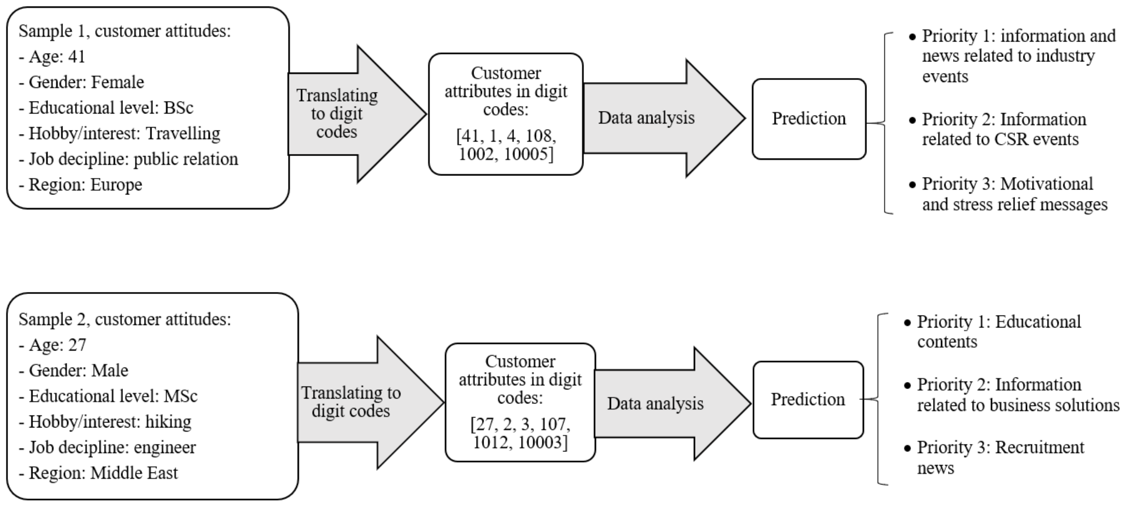

Figure. 3. Recommended content types predicted by the model for two hypothetical samples

To implement the model, we first selected 10 individual business customers from the customer database of the energy company through purposive sampling. The samples were selected with different ages (22 to 63), genders (five men, five women), educational levels (undergraduate to Ph.D.), job disciplines (from seven different job disciplines), and regions (from four different regions). We conducted five rounds of trials. In each round, the proposed contents of the model were sent to customers. Next, they were asked to submit their feedback about the relevance and value of the proposed content.

5.4. The model evaluation and improvement using the customer feedback

The level of customer satisfaction was evaluated using a five-emoji Likert questionnaire (i.e., ranging from very dissatisfied to very satisfied). Each time, the feedback was used to update the customers' database as well as data training for the model. In cases where the customer feedback did not confirm satisfaction with the PIS recommendations (i.e., scores below 4), human experts were employed to analyze the customer feedback. At this stage, if needed, experts could also make direct contact with customers (using email or phone) to talk with them directly and understand what are their content preferences (i.e., preferred U&G-based content types) and then include their preferences in the database. Here, human involvement helps reduce ML bias by ensuring that the ML technique is enacted fairly and that content aligns with the customer's actual preferences. This process also helps ensure that the employed attributes are appropriate for the specific purpose of the PIS. Furthermore, for customers who do not like to include their sensitive personal information (e.g., gender, region) in their profile, making direct contact can help to ensure the correct content preferences are included in the customer database.

After conducting the five rounds of feedback collection, the accuracy of the model was calculated. In this study, we evaluated the accuracy of the ML-based PIS using the Precision, Recall, and F1 metrics. Precision, recall, and F1 are among the most common evaluation metrics (Chen and Liu, 2017; Wang and Yin, 2012). Precision is defined as the ratio of relevant items to proposed (recommended) items. Recall is the proportion of relevant items that have been proposed (recommended) to the total number of relevant items (Wang and Yin, 2012). F1 is the weighted average of precision and recall (Chen and Liu, 2017).

Precision and recall were computed from a table, such as the one shown in Table 5.

Table 5

Next, we can compute the following equations:

1) $$\text{Precision} = \frac{Nrp}{Np}$$

$$\text{Np} = \text{Nrp} + \text{Nip}$$

2) $$\text{Recall} = \frac{Nrp}{Nr}$$

$$\text{Nr} = \text{Nrp} + \text{Nrn}$$

3) $$\text{F1} = \frac{2Precision.Recall}{Precision+Recall}$$

Table 6 indicates the computed amounts of Precision, Recall, and F1 for the PIS model after 10, 20, 30, 40, and 50 recommendations.

Table 6

Acceptable scores for Precision, Recall, or F1 are not unique for different purposes. In some cases, like disease diagnosis systems, researchers need a precision or recall score greater than 0.9 to make sure that the predictions are highly precise. However, for most marketing purposes such as creating a PIS, precision, recall, or F1 scores of above 0.5 are acceptable. The computed Precision, Recall, and F1 scores in this research were 0.73, 0.72, and 0.72 respectively, all are above 0.5 and therefore are acceptable (see Table 6). Thus, the results confirmed the predictive power of the integrated human-ML model for the specific purpose of this research.

6. Discussions and conclusions

While ML techniques surpass humans' ability to accomplish some quantitative targets with computable criteria (Parry et al., 2016), humans typically outperform ML in subjective and qualitative evaluations due to their insights and intuitive capabilities (Jarrahi, 2018).

Given the key stages of the CRISP-DM standard data mining model, and in light of the findings of our empirical research and the main stages of our research framework, we present the research model (see Figure 4). The model illustrates how human involvement can augment ML in each of the five main stages of the data mining standard model (i.e., business/market understanding, data understanding, data preparation, model creation and deployment, and model evaluation) in order to create the PIS model for business customers.

In this regard, the model proposes human involvement in 1) business/market understanding phase: in this phase, the model suggests employing B2B marketing experts to develop a theoretical underpinning (e.g., by using the U&G theory) for the PIS model considering the business context and findings of previous research, 2) Data understanding phase: the model proposes a) serve the domain expertise of IT experts and B2B experts to select the most appropriate ML techniques, b) to use the tactic knowledge of B2B experts to conduct initial feature selection to augment ML-based feature selection techniques. Human contributions in phases 1 and 2 not only help create a theoretical basis to "understand the market" and customers' information preferences but can also help identify influential features thus facilitating the "data understanding" stage. Hence, implementation of the first two phases of our model is essential to establish a robust foundation to create the PIS; 3) data collection and preparation phase: the model proposes to employ marketing experts to collect data from B2B respondents. This involvement can help B2B firms establish organized databases. 4) model creation and deployment phase: in this phase, human expertise can be used to leverage coding languages for creating the PIS model regarding the specific needs of B2B firms; 5) the model evaluation and improvement phase: the model suggests integrating human judgment with ML computing power to improve the accuracy of the ML-based PIS. While customers' feedback with high satisfaction scores is directly submitted to the customer data, for customers' feedback with low satisfaction scores, the model proposes a) to employ marketing experts to evaluate the customers' feedback, b) if required, marketing experts can make direct contact with customers to identify their exact content preferences.

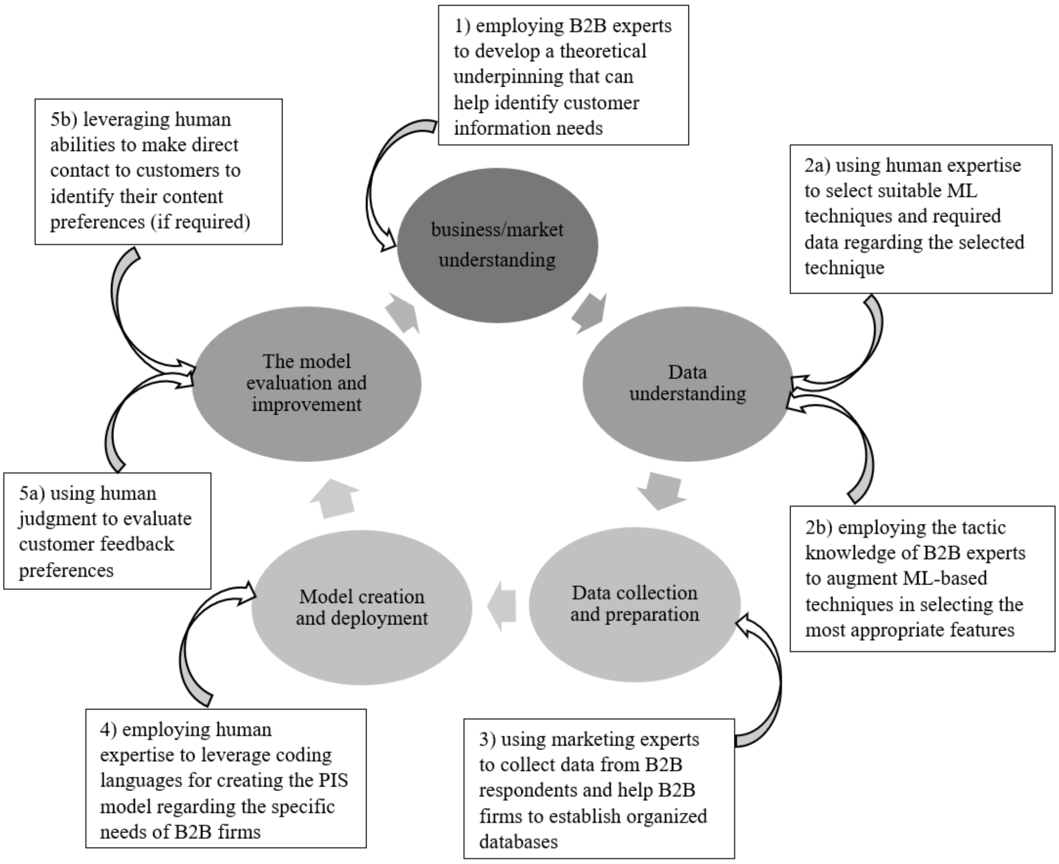

Figure. 4. Model of human involvement to augment ML to create a PIS for business customers

7. Implications, and future directions

This study enumerates the key factors that may elevate the performance of integrated human–ML models with a focus on B2B personalization. The article also offers important theoretical and managerial implications and some suggestions for future research.

7.1.Theoretical Implications

The findings of the present article suggest several theoretical implications. First, in response to the dearth of literature on human-ML augmentation, the current study bridges the gap between theory and practice by proposing an integrated human-ML model to develop a PIS for business customers. Given the fact that humans still hold the upper hand in dealing with contradictory or uncertain information and the relationship-building aspects of the business that are paramount in B2B ecosystems (Latinovic and Chatterjee, 2022), and regarding the potential contributions of human experts to reinforce the ML-based models (See Section 2), the article presents an integrated human-ML framework (See Figure 1). Based on the stages of developing the PIS proposed in the methods section (i.e., Section 4), we developed an integrated human-ML PIS (See Section 5). Next, in light of the findings of previous sections and using the key stages of the CRISP-DM standard data mining model (i.e., business/market understanding, data understanding, data preparation, model creation and deployment, and model evaluation), the article presents the research model (See Figure 4). This model can be used by B2B firms as a guide to developing an efficient PIS to meet the growing expectations of B2B customers for receiving personalized experiences (Kessinger, 2022) and relevant information (Sun et al., 2019).

Second, we highlight the significant effect of using appropriate marketing theories to establish a cornerstone for the creation of integrated human-ML models. Because theories can shape a robust foundation that guides a research design to draw insights. They can also increase the interpretability of the model's outputs (Ma and Sun, 2020). This research suggests the U&G theory to identify different content types that are valuable or engaging for individual business customers and thus can be relevant to their preferences. B2B marketers can then use the U&G theory to interpret and include customer feedback to improve the PIS over time.

Third, our findings concur with existing decision-making theories such as heuristics theory that emphasizes the significant role of employing human insights and tactic knowledge to understand the context in which a problem has arisen (Fantino and Stolarz-Fantino, 2005; Zerilli et al., 2019) because years of experience in performing qualitative assessments empower human experts to select features, solutions, and methods that suit the unique context in which a problem is embedded. In other words, notwithstanding the approved abilities of AI and ML techniques to transform customer data into useful information and knowledge (Paschen et al., 2019) and make informed decisions (Farrokhi et al., 2020), human decision-makers mainly make choices by applying insights and qualitative assessment rooted in years of tacit experience and personal judgment (Jarrahi, 2018). We, therefore, argue that injecting human insights into an ML-based model could help consider real-world complexities to identify customers' real needs and preferences, thus augmenting the data-driven perspective of ML-based models for offering a more advanced shape of B2B personalization.

Finally, our study sheds light on the "dark side" of ML, which leads to unfair or biased results (Wang et al., 2020; Akter et al., 2021). Uncertainty always surrounds the appropriateness or importance of some features used in a model, especially concerning sensitive attributes such as gender, nationality, and region. For example, one of the first questions asked about selected features in the current research is whether *gender* is the right attribute for a model designed specifically for a B2B context. It should be considered that while some recent studies have sought to remove bias from learning algorithms, they have largely ignored how the effect of some features—such as gender—may be embedded in human needs and preferences. Making decisions in this regard becomes more difficult, especially when previous studies failed to address the impact of the feature on the research subject. For instance, limited information is available about the relationship between gender and preferences for different content types, especially in B2B contexts. In such cases, we also believe that using tacit knowledge can help select more appropriate attributes, including sensitive features.

7.2. Practical implications

This article offers four key practical implications. First, B2B personalization drives data-driven content experiences that help confirm fit with customer needs (Forrester, 2023). Therefore, to implement modern B2B marketing methods such as account-based marketing, which are highly dependent on the deployment of efficient personalization and ML techniques (Burgess and Munn, 2021; Golec et al., 2019), the use of advanced ML models (e.g., integrated human-ML models) can help firms improve their communication efforts to offer customized content and recommendations, and bespoke solutions (Gene Day and Wei Shi, 2020) based on the specific needs of B2B customers.

Second, due to the growing importance of ML techniques to predict and fulfill the exact needs of business customers (Lin et al., 2022) and the unparalleled human capabilities in evaluating subjective and qualitative matters (Jarrahi, 2018; Latinovic and Chatterjee, 2022) which are vital for building strong B2B relationships; the authors argue that the future of B2B marketing hinges strongly on leveraging integrated human-ML models that use ML capabilities as well as human insights to provide personalized services for business customers.

Third, a convincing consensus has been established among researchers that the future sources of competitive advantage for organizations depend on the extent to which they can safely and securely deploy bias-free AI and ML-based solutions to manage and solve critical business problems (Akter et al., 2021). As part of the de-biasing strategy, using expert judgment to evaluate customer feedback can reduce potential algorithm bias. In this context, B2B marketing experts can especially help draw the required insights to improve the model through continuous assessments of customer feedback.

Finally, our findings confirmed the results of previous research in that applying ML techniques is not merely a simple technical issue and requires seamless synergy between human knowledge and ML computing power, enabling them to work cooperatively (Dwivedi et al., 2019). Therefore, B2B organizations need to pay particular attention to incorporating the knowledge of marketing experts and theorists as well as IT and ML experts to create efficient personalized services (e.g., the PIS).

7.3. Limitations and future directions

The article presents a novel approach to offering personalized content to individual business customers, thus contributing to B2B personalization theory, and account-based marketing literature, which is firmly based on the use of customized marketing and personalization models (Golec et al., 2019; Burgess and Munn, 2021). Given the growing importance of personalized services (e.g., personalized content, newsletters, recommendations, chats, emails) and the increasing use of account-based marketing by B2B firms (Burgess and Munn, 2021) due to the growing demands of business customers to receive personalized experiences (Kessinger, 2022), further research is needed to bridge the gap between theoretical and practical aspects of B2B personalization.

Furthermore, this paper offers an understanding of potential human contributions to augment ML techniques and practically demonstrates how to develop an integrated human-ML model to create a PIS for business customers. Future research can work on recognizing other critical touchpoints where humans can augment ML techniques, for example, situations in which know-how acquired by B2B practitioners cannot be replaced by ML techniques. We also believe further research is needed to provide additional support about when or in which conditions using human insights or ML techniques leads to more accurate, reliable, and fairer results.

Although hybrid human-ML models have shown remarkable potential to shape enhanced intelligence to solve B2B problems (Karlinsky-Shichor and Netzer, 2023), further studies are needed to develop the theoretical underpinning of such models. We thus recommend future research to investigate the theoretical aspects of human-ML models considering data mining processes (e.g., CRISP-DM and SEMMA), decision-making theories (e.g., heuristics theory, prospect Theory), social computing approaches, and relevant theories to the specific field of research (e.g., U&G theory in our study).

Finally, considering the limitation of data in most B2B contexts in comparison with B2C environments, this research collected data from visitors of industry events. Although using this method led to collecting well-structured data, taking this approach requires lots of time and resources; therefore, it is suggested to conduct further research for deriving business customers' insights from different data channels as well as extract knowledge and insights from customer-generated content in B2B contexts.

References

Abbasi, F., Khadivar, A., and Yazdinejad, M. (2019), "A Grouping Hotel Recommender System Based on Deep Learning and Sentiment Analysis", *Journal of Information Technology Management*, Vol. 11 No. 2, pp. 59-78.

Akter, S., Dwivedi, Y. K., Biswas, K., Michael, K., Bandara, R. J., and Sajib, S. (2021), "Addressing algorithmic bias in AI-driven customer management", *Journal of Global Information Management*, Vol. 29 No. 6, pp. 1-27.

Ali, O. (2019), "EY research: countdown to a 'new energy world' faster than expected",. Available at: https://www.power-technology.com/news/ey-research-energy/.(Accessed July 2019).

Alvarez Dominguez, A. (2011), "The impact of human resource disclosure on corporate image", *Journal of Human Resource Costing & Accounting*, Vol. 15 No. 4, pp. 279-298.

Andersson, S. and Wikström, N. (2017), "Why and how are social media used in a B2B context, and which stakeholders are involved?", *Journal of Business & Industrial Marketing*, Vol. 32 No. 8, pp. 1098-1108. https://doi.org/10.1108/JBIM-07-2016-0148.

Ayele, W. Y. (2020), "Adapting CRISP-DM for idea mining: a data mining process for generating ideas using a textual dataset", *International Journal of Advanced Computer Sciences and Applications*, Vol, 11, No. 6, pp. 20-32.

Ansari, F., Erol, S., and Sihn, W. (2018), “Rethinking human-machine learning in industry 4.0: how does the paradigm shift treat the role of human learning?”, *Procedia Manufacturing*, Vol. 23, pp. 117-122.

Barro, S., and Davenport, T. H. (2019), “People and machines: Partners in innovation”, *MIT Sloan Management Review*, Vol. 60 No. 4, pp. 22–28.

Brown, R. (2019), “What are Features in Machine Learning and Why it is Important?.”, available at: https://cogitotech.medium.com/what-are-features-in-machine-learning-and-why-it-is-important-e72f9905b54d. (Accessed, July 2019).

Brownlee, J. (2019), “How to Choose a Feature Selection Method For Machine Learning. available at: https://machinelearningmastery.com/feature-selection-with-real-and-categorical-data/.(Accessed November 2019).

Bruhn, M., Schnebelen, S., and Schäfer, D. (2014), “Antecedents and consequences of the quality of e-customer-to-customer interactions in B2B brand communities”, *Industrial Marketing Management*, Vol. 43, No. 1, pp.164–176.

Brunke, L., Greeff, M., Hall, A. W., Yuan, Z., Zhou, S., Panerati, J., and Schoellig, A. P. (2022), “Safe learning in robotics: From learning-based control to safe reinforcement learning”, *Annual Review of Control, Robotics, and Autonomous Systems*, Vol. 5, pp. 411-444.

Burgess, B., and Munn, D. (2021), *Practitioner's guide to account-based marketing*, Kogan Page Limited, United Kingdom, London.

Chen, M., and Liu, P. (2017), “Performance evaluation of recommender systems”, *International Journal of Performability Engineering*, Vol. 13 No. 8, pp. 1246.

Chen, L., Jiang, M., Jia, F. and Liu, G. (2022), “Artificial intelligence adoption in business-to-business marketing: toward a conceptual framework”, *Journal of Business & Industrial Marketing*, Vol. 37 No. 5, pp. 1025-1044. https://doi.org/10.1108/JBIM-09-2020-0448.

Cheng, T.H., Wei, C.P., and Tseng, V. S. (2006), "Feature Selection for Medical Data Mining: Comparisons of Expert Judgment and Automatic Approaches", *19th IEEE Symposium on Computer-Based Medical Systems*. 165-170, https://doi.org/10.1109/CBMS.2006.87.

Christopher, M. V., and Marder, B. (2017), "An Exploration of the Uses and Gratifications of Social Media as Part of B2B Processes: Decision Makers vs. Marketers"—A Structured Abstract. In *Creating Marketing Magic and Innovative Future Marketing Trends*. pp.1407-1412). Springer, Cham.

Chui, M., Manyika, J., Miremadi, M., Henke, N., Chung, R., Nel, P., and Malhotra, S. (2018), "Notes from the AI frontier: Applications and value of deep learning. McKinsey global institute discussion paper", Available at: https://www.mckinsey.com/featured-insights/artificial-intelligence/notes-from-the-aifrontier-applications-and-value-of-deep-learning. (Accessed June 12, 2019).

Cortez, R. M., and Johnston, W. J. (2017), "The future of B2B marketing theory: A historical and prospective analysis", *Industrial Marketing Management*, Vol. 66, pp. 90-102.

Collingwood, L., and Wilkerson, J. (2012), "Tradeoffs in Accuracy and Efficiency in Supervised Learning Methods", *Journal of Information Technology & Politics*, Vol. 9 No. 3, pp. 298-318.

Davenport, T., Guha, A., Grewal, D. et al. (2020), "How artificial intelligence will change the future of marketing", *Journal of the Academy of Marketing Science*, Vol. 48, pp. 24–42. https://doi.org/10.1007/s11747-019-00696-0.

Gene Day, D., and Wei Shi, S. (2020), "Automated and Scalable: Account-Based B2B Marketing for Startup Companies", *Journal of Business Theory and Practice*, Vol. 8, No. 2, pp.16-23.

Deng, W., Shi, Y., Chen, Z., Kwak, W., and Tang, H. (2020), "Recommender system for marketing optimization", *World Wide Web*, Vol. 23, pp.1497–1517.

Di Mauro, M., Galatro, G., Fortino, G., and Liotta, A. (2021), "Supervised feature selection techniques in network intrusion detection: A critical review", *Engineering Applications of Artificial Intelligence*, Vol. 101, pp. 104216.

Dwivedi, Y.K., Rana, N.P., Jeyaraj, A. et al. (2019), "Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a Revised Theoretical Model", *Information Systems Frontiers*, Vol. 21, pp.719–734.

Edvardsson, B., Kristensson, P., Magnusson, P., and Sundström, E. (2012), "Customer integration within service development - a review of methods and an analysis of insitu and exsitu contributions", *Technovation*, Vol. 32, pp. 419–429.

Esmaieeli Sikaroudi, A. M., Ghousi, R., and Sikaroudi, A. (2015), "A data mining approach to employee turnover prediction (case study: Arak automotive parts manufacturing)." *Journal of industrial and systems engineering*, Vol. 8, No. 4, pp. 106-121.

Fantino, E., and Stolarz-Fantino, S. (2005), "Decision-making: Context matters", *Behavioural Processes,* Vol. 69 No. 2, pp.165-171.

Farrokhi, A., Shirazi, F., Hajli, N., and Tajvidi, M. (2020), "Using artificial intelligence to detect crisis related to events: Decision making in B2B by artificial intelligence", *Industrial Marketing Management*, Vol. 91, pp. 257-273. https://doi.org/10.1016/j.indmarman.2020.09.015.

Forrester (2023), "Unlocking The Power Of B2B Personalization". https://www.forbes.com/sites/forrester/2023/04/25/unlocking-the-power-of-b2b-personalization/?sh=2d2919607d72.

Gartner (2021), "Emerging Technologies Are Key to Executing an Effective Personalization Strategy for Digital Marketing". https://www.gartner.com/en/newsroom/press-releases/-gartner-says-63--of-digital-marketing-leaders-still-struggle-wi.

Gillooly, L., Crowther, P. and Medway, D. (2017), “Experiential sponsorship activation at a sports mega-event: the case of Cisco at London 2012”, *Sport, Business and Management*, Vol. 7 No. 4, pp. 404-425. https://doi.org/10.1108/SBM-04-2016-0015.

Golec, C., Isaacson, P., and Fewless, J. (2019), *Account-based Marketing: How to Target and Engage the Companies that Will Grow Your Revenue*. John Wiley & Sons. Hoboken, New Jersey.

Gopalakrishna, S., Malthouse, E. and Lawrence, J. (2019), “Managing customer engagement at trade shows”, *Industrial Marketing Management*, Vol. 81, pp. 99-114. https://doi.org/10.1016/j.indmarman.2017.11.015.

Graef, R., Klier, M., Kluge, K., and Zolitschka, J.F. (2020), “Human-machine collaboration in online customer service – a long-term feedback-based approach”, *Electronic Markets*. https://doi.org/10.1007/s12525-020-00420-9.

Gregory, R. W., Henfridsson, O., Kaganer, E., and Kyriakou, H. (2020), “The role of artificial intelligence and data network effects for creating user value”, *Academy of Management Review*. https://doi.org/10.5465/amr.2019.0178.

Grissa, K. (2017), “What “uses and gratifications” theory can tell us about using professional networking sites (EG LinkedIn, Viadeo, Xing, SkilledAfricans, Plaxo…)”, In *International Conference on Digital Economy* (pp. 15-28). Springer, Cham.

Haji Habibi, F., Hamilton, C.A., Valos, M.J. and Callaghan, M. (2015), “E-marketing orientation and social media implementation in B2B marketing”, *European Business Review*, Vol. 27 No. 6, pp. 638-655. https://doi.org/10.1108/EBR-03-2015-0026.

Hagen, et al. (2020), “How can machine learning aid behavioral marketing research?”, *Marketing Letters*, https://doi.org/10.1007/s11002-020-09535-7.

Hagendorff, T. (2019), ”From privacy to anti-discrimination in times of machine learning”, *Ethics and Information Technology*, Vol. 21, No. 4, pp. 331-343.

Hollebeek, L.D. (2019), “Developing business customer engagement through social media engagement-platforms: An integrative S-D logic/RBV-informed model”, *Industrial Marketing Management*, Vol. 81, pp. 89-98.

Hotz, N. (2022), “What is CRISP DM?”, available at: https://www.datascience-pm.com/crisp-dm-2/.

Hristova, G. (2013), *Content marketing for Business to Business*, Namics AG, Bederstrasse. 18002 Zurich.

Huber, S., Wiemer, H., Schneider, D., and Ihlenfeldt, S. (2019). DMME: Data mining methodology for engineering applications–a holistic extension to the CRISP-DM mod-el. Procedia Cirp, 79, 403-408.

Hunter, F. (2020), “Human Rights Commission warns government over ‘dangerous’ use of AI”, Available at: https://www.smh.com.au/politics/federal/human-rights-commission-warns-government-over-dangerous-use-of-ai-20200813-p55lgn.html.

Isinkaye, F. O., Folajimi, Y. O., and Ojokoh, B. A. (2015), “Recommendation systems: Principles, methods and evaluation”, *Egyptian informatics journal*, Vol. 16 No. 3, pp. 261-273.

Izadi, B., Ranjbarian, B., and Ketabi, S. (2013). “Performance Analysis of Classification Methods and Alternative Linear Programming Integrated with Fuzzy Delphi Feature Selection”, *Information Technology and Computer Science*, Vol. 10, pp. 9-20. https://doi.org/10.5815/ijitcs.2013.10.02.

Jain, G., Paul, J., and Shrivastava, A. (2021), “Hyper-personalization, co-creation, digital clienteling and transformation”, *Journal of Business Research*, Vol. 124, pp. 12–23. https://doi.org/10.1016/j.jbusres.2020.11.034.

Jarrahi, M. H. (2018), “Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making”, *Business horizons*, Vol. 61 No. 4, pp. 577-586.

Järvinen, J., and Taiminen, H. (2016), “Harnessing marketing automation for B2B content marketing”, *Industrial Marketing Management*, Vol. 54, pp. 164-175.

Kaplan, A., and Haenlein, M. (2020), “Rulers of the world, unite! The challenges and opportunities of artificial intelligence”, *Business Horizons*, Vol. 63, pp. 37-50.

Karlinsky-Shichor, Y., and Netzer, O. (2023), “Automating the b2b salesperson pricing decisions: A human-machine hybrid approach”, *Marketing Science*. https://doi.org/10.1287/mksc.2023.1449.

Katz, E., Gurevitch, M., and Haas, H. (1973), “On the use of the mass media for important things”, *American Sociological Review*, Vol. 38, No. 2, pp.164e181.

Kessinger, J. (2022), “The Need for B2B Personalization is Growing: What You Should Be Doing to Create an Unforgettable Account Experience”, available at: https://www.hushly.com/blog/b2b-personalization/.

Khosrow-Pour, M. (2008), *Encyclopedia of Information Science and Technology*. Second Edition, Information Science Reference, New York. USA.

Klaus, P. (2013), “The case of Amazon.com: towards a conceptual framework of online customer service experience (OCSE) using the emerging consensus technique (ECT)”, *Journal of Services Marketing*, Vol. 47 No. 6, pp. 433-457.

Kleinberg, J. M., Mullainathan, S., and Raghavan, M. (2016), “Inherent trade-ofs in the fair determination of risk scores (1–23)”, available at: https://arxiv.org/abs/1609.05807v2.

Kühl, N., Schemmer, M., Goutier, M., and Satzger, G. (2022), “Artificial intelligence and machine learning”, *Electronic Markets*, https://doi.org/10.1007/s12525-022-00598-0.

Latinovic, Z., and Chatterjee, S. C. (2022), “Achieving the promise of AI and ML in delivering economic and relational customer value in B2B”, *Journal of Business Research*, Vol. 144, pp. 966-974. https://doi.org/10.1016/j.jbusres.2022.01.052.

Lee, I., and Shin, Y.J. (2020), “Machine learning for enterprises: Applications, algorithm selection, and challenges”, *Business Horizons*, Vol. 63 No. 2, pp. 157-170.

Lieder, F., Plunkett, D., Hamrick, J. B., Russell, S. J., Hay, N., and Griffiths, T. (2014), “Algorithm selection by rational metareasoning as a model of human strategy selection”, *Proceedings of the 27th International Conference on Neural Information Processing Systems,* pp. 2870–2878.

Lilien, G. L. (2016), “The B2B knowledge gap”, *International Journal of Research in Marketing*, Vol. 33, No. 3, pp. 543-556.

Lin, X., Shao, B., and Wang, X. (2022), “Employees' perceptions of chatbots in B2B marketing: Affordances vs. disaffordances”, *Industrial Marketing Management*, Vol. 101, pp. 45-56.

Liu, X. (2020), “Analyzing the impact of user-generated content on B2B Firms' stock performance: Big data analysis with machine learning methods”, *Industrial Marketing Management*, Vol. 86, pp. 30-39.

Logesh, R. and Subramaniyaswam, V. (2019), “Exploring Hybrid Recommender Systems for Personalized Travel Applications”, *Cognitive Informatics and Soft Computing*, Vol. 768, pp. 535-544.

Ma, L., and Sun, B. (2020), “Machine learning and AI in marketing – Connecting computing power to human insights”, *International Journal of Research in Marketing*, Vol. 37 No. 3, pp. 481-504.

Mehrabi, N., Morstatter, F., Saxena, N., Lerman, K., and Galstyan, A. (2021), “A survey on bias and fairness in machine learning”, *ACM Computing Surveys* (CSUR), Vol. 54 No. 6, pp.1-35.

Mero, J., Leinonen, M., Makkonen, H., and Karjaluoto, H. (2022), “Agile logic for SaaS implementation: Capitalizing on marketing automation software in a start-up”, *Journal of Business Research*, Vol. 145, pp. 583–594. https://doi.org/10.1016/j.jbusres.2022.03.026.

McLean, G. J. (2017), “Investigating the online customer experience – a B2B perspective”, *Marketing Intelligence & Planning*, Vol. 35 No. 5, pp. 657–672.

Murphy, M., and Sashi, C. M. (2018), “Communication, interactivity, and satisfaction in B2B relationships”, *Industrial Marketing Management*, Vol. 68, pp. 1-12.

Nayak, B.C., Nayak, G.K. and Jena, D. (2020), “Social recognition and employee engagement: The effect of social media in organizations”, *International Journal of Engineering Business Management*, 12, 1847979020975109. https://doi.org/10.1177/1847979020975109.

Ng, M. F., Zhao, J., Yan, Q., Conduit, G. J., and Seh, Z. W. (2020), “Predicting the state of charge and health of batteries using data-driven machine learning”, *Nature Machine Intelligence*, Vol. 2 No.3, pp.161-170.

Pandey, N., Nayal, P., and Rathore, A. S. (2020), “Digital marketing for B2B organizations: structured literature review and future research directions”, *Journal of Business & Industrial Marketing*, Vol. 35, No. 7, pp. 1191-1204.

Papagiannidis, E., Mikalef, P., Conboy, K., and Van de Wetering, R. (2023), “Uncovering the dark side of AI-based decision-making: A case study in a B2B context”, *Industrial Marketing Management*, Vol. 115, pp. 253-265. https://doi.org/10.1016/j.indmarman.2023.10.003.

Parry, K., Cohen M., and Bhattacharya, S. (2016), “Rise of the machines: A critical consideration of automated leadership decision making in organizations”, *Group and Organization Management*, Vol. 41 No. 5, pp. 571—594.

Paschen, J., Kietzmann, J. and Kietzmann, T.C. (2019), "Artificial intelligence (AI) and its implications for market knowledge in B2B marketing", *Journal of Business & Industrial Marketing*, Vol. 34 No. 7, pp. 1410-1419. https://doi.org/10.1108/JBIM-10-2018-0295.

Rancati, E. and Gordini, N. (2014), "Content marketing metrics: theoretical aspects and empirical evidence," *European Scientific Journal,* Vol. 10 No. 34, pp. 92-104.

Rietveld, R., Dolen, W.D., Mazloom, M., and Worring, M. (2020). "What You Feel, Is What You Like Influence of Message Appeals on Customer Engagement on Instagram", *Journal of Interactive marketing*, Vol. 49, pp. 20-53.

Sattar, A., Ghazanfar, M.A., and Iqbal, M. (2017), "Building Accurate and Practical Recommender System", *Computer Engineering and Computer Science*, Vol. 42, pp. 3229–3247.

Saura, J.R., Palos-Sanchez, P. and Blanco-González, A. (2020), "The importance of information service offerings of collaborative CRMs on decision-making in B2B marketing", *Journal of Business & Industrial Marketing*, Vol. 35 No. 3, pp. 470-482.

Schäfer, F., Zeiselmair, C., Becker, J., and Otten, H. (2018), "Synthesizing CRISP-DM and quality management: A data mining approach for production processes", *IEEE International Conference on Technology Management, Operations and Decisions (ICTMOD)* pp. 190-195.

Shearer, C. (2000), "The CRISP-DM model: the new blueprint for data mining", J Data Warehousing, Vol. 5, pp.13—22.

Sheikhpour, R., Sarram, M. A., Gharaghani, S., and Chahooki, M. A. Z. (2017), "A survey on semi-supervised feature selection methods *Pattern Recognition,* Vol. 64, pp. 141-158.

Smallcombe, M. (2022), "Big Data Analytics in B2B E-Commerce: What It Is and Why You Need It", available at: https://www.integrate.io/blog/big-data-analytics-in-b2b-ecommerce/.(Accessed May 2022).

Sun, L., Guo, J., and Zhu, Y. (2019), “Applying uncertainty theory into the restaurant recommender system based on sentiment analysis of online Chinese reviews”, *WorldWide Web*, Vol. 22, pp. 83–100.

Sun, W., Nasraoui, O., and Shafto, P. (2020), “Evolution and impact of bias in human and machine learning algorithm interaction”, *Plos one*, Vol. 15 No. 8), e0235502. https://doi.org/10.1371/journal.pone.0235502.

Sundström, M., Alm, K.H., Larsson, N., and Dahlin, O. (2020), “B2B social media content: engagement on LinkedIn”, *Journal of Business & Industrial Marketing*, https://doi.org/10.1108/JBIM-02-2020-0078.

Tahmasebi, F., Meghdadi, M., Ahmadian, S., and Valiallahi, K. (2021), “A hybrid recommendation system based on profile expansion technique to alleviate cold start problem”, *Multimedia Tools and Applications*, Vol. 80 No. 2, pp. 2339-2354.

Taiminen, K. and Ranaweera, C. (2019), 3Fostering brand engagement and value-laden trusted B2B relationships through digital content marketing: The role of brand’s helpfulness”, *European Journal of Marketing*, Vol. 53 No. 9, pp. 1759-1781. https://doi.org/10.1108/EJM-10-2017-0794.

Teodorescu, M. H., Morse, L., Awwad, Y., and Kane, G. C. (2021), “Failures of fairness in automation require a deeper understanding of Human-ML augmentation”, *MIS Quarterly*, Vol. 45 No. 3. pp. 1-18.

Vazan, P., Janikova, D., Tanuska, P., Kebisek, M., and Cervenanska, Z. (2017), “Using data mining methods for manufacturing process control”, *IFAC-PapersOnLine*, Vol. 50, No. 1, pp. 6178-6183.

Vesal, M., Siahtiri, V. and O'Cass, A. (2020), “Strengthening B2B brands by signalling environmental sustainability and managing customer relationships”, *Industrial Marketing Management*, Vol. 92, pp. 321-331. https://doi.org/10.1016/j.indmarman.2020.02.024.

Vijayan, j. (2019), "our Ways AI Can Augment Human Capabilities", https://www.informationweek.com/ai-or-machine-learning/four-ways-ai-can-augment-human-capabilities. (Accessed September 2019)

Villarroel Ordenes, F., and Silipo, R. (2021), "Machine learning for marketing on the KNIME Hub: The development of a live repository for marketing applications", *Journal of Business Research*, Vol. 137, pp. 393–410. http://doi.org/10.1016/j.jbusres.2021.08.036.

Wang, Y.Y., Luse, A., Townsend, A.M., and Mennecke, B.E. (2014), "Understanding the moderating roles of types of recommender systems and products on customer behavioral intention to use recommender systems", *Inf Syst E-Bus Manage*, https://doi.org/10.1007/s10257-014-0269-9.

Wang, J., and Yin, J. (2012), "Enhancing accuracy of user-based collaborative filtering recommendation algorithm in social network", *3rd International Conference on System Science*, *Engineering Design and Manufacturing Informatization*, Chengdu, China, 20 - 21 October.

Wang, R., Harper, F. M., and Zhu, H. (2020), "Factors Influencing Perceived Fairness in Algorithmic Decision-Making: Algorithm Outcomes, Development Procedures, and Individual Differences", *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3313831.3376813.

Wilson, H. J., and Daugherty, P. R. (2018), "Collaborative intelligence: Humans and AI are joining forces", *Harvard Business Review*, Vol. 96 No. 4, pp. 114-123.

Wirtz, B. W., Weyerer, J. C., and Sturm, B. J. (2020), "The dark sides of artificial intelligence: An integrated AI governance framework for public administration", *International Journal of Public Administration*, Vol. 43 No. 9, pp. 818–829.

Yaghtin, S., Safarzadeh, H., and Karimi Zand, M. (2020), “Planning a goal-oriented B2B content marketing strategy”, *Marketing Intelligence & Planning*, Vol. 38 No. 7, pp. 1007-1012. https://doi.org/10.1108/MIP-11-2019-0559.

Yaghtin, S. (2021). Sustainable B2B marketing during a pandemic crisis: An overview of sustainable solutions and marketing practices, (Ed), Co-creating the Post COVID-19 World: Exploring Sustainable Paths, Arab Open University, pp.50-66.

Yaghtin, S., Safarzadeh, H. and Karimi Zand, M. (2021), “B2B digital content marketing in uncertain situations: a systematic review”, *Journal of Business & Industrial Marketing*, Vol. 37 No. 9, pp. 1852-1866. https://doi.org/10.1108/JBIM-03-2021-0174.

Zacharias, J., von Zahn, M., Chen, J., and Hinz, O. (2022), “Designing a feature selection method based on explainable artificial intelligence”, *Electronic Markets*, https://doi.org/10.1007/s12525-022-00608-1.

Zerilli, J., Knott, A., Maclaurin, J., and Gavaghan, C. (2019), “Algorithmic decision-making and the control problem”, *Minds and Machines*, Vol. 29 No. 4, pp. 555-578.

Zhai, Y., Yang, K., Chen, L., Lin, H., Yu, M. and Jin, R. (2023), “Digital entrepreneurship: global maps and trends of research”, *Journal of Business & Industrial Marketing*, Vol. 38 No. 3, pp. 637-655. https://doi.org/10.1108/JBIM-05-2021-0244;

Ziarani, R. J., and Ravanmehr, R. (2021), “Deep neural network approach for a serendipity-oriented recommendation system”, *Expert Systems with Applications*, Vol. 185, 115660. https://10.1016/j.eswa.2021.115660.