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Identifying User Innovations through AI in Online Communities– A Transfer Learning Approach

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Completed Research Paper

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Abstract

Identifying innovative users and their ideas is crucial, for example, in crowdsourcing. But, analyzing large amounts of unstructured textual data from such online communities poses a challenge for organizations. Therefore, researchers started developing automated approaches to identify innovative users. Our study introduces an advanced machine-learning approach that minimizes manual work by combining transfer learning with a transformer-based design. We train the model on separate datasets, including an online maker community and various internet texts. The maker community posts represent need-solution pairs, which express needs and describe fitting prototypes. Then, we transfer the model and identify potential user innovations in a kitesurfing community. We validate the identified posts by manually checking a subsample and analyzing how words affect the model's classification decision. This study contributes to the growing portfolio of user innovation identification by combining state-of-the-art natural language processing and transfer learning to improve automated identification.

Keywords: User Innovation Identification, Artificial Intelligence, Transfer Learning, Online Communities, Natural Language Processing

Introduction

On the platform Lego Ideas, Lego sources and screens thousands of ideas simultaneously (Lego Ideas). Lego users continuously propose new designs, and Lego poses additional challenges to inspire the platform members. Such crowdsourcing forms leverage a large group's collective intelligence and expertise, typically in the form of online communities. External knowledge, particularly from users of products and services, has long been recognized as a critical source of potential innovations for firms (Afuah and Tucci 2012; Dahlander et al. 2016; Fisher 2019; Hippel 2017; Laursen and Salter 2006). Being at the forefront of product interaction, these users often identify needs and conceptualize solutions that could have commercial implications (Baldwin et al. 2006; Franke et al. 2006; Hippel 2017; Jensen et al. 2014). The underlying premise is that a diverse group of individuals can, in many instances, produce more innovative solutions or better information than a closed team of specialists (Pollok et al. 2021).

Similarly, other kinds of online communities, like forums or expertise-related platforms without explicit company interference, bear innovative ideas and discuss product suggestions (Dahlander and Frederiksen 2011; Safadi et al. 2021). Online communities, which have experienced steady growth over the years, have become significant venues where such user innovations can be observed and harnessed. Within these platforms, users not only communicate and collaborate but often voluntarily disclose their innovative ideas and solutions (Dahlander and Frederiksen 2011; Hippel and Krogh 2006; Jeppesen and Frederiksen 2006; Kratzer et al. 2016; Resch and Kock 2021).

Individuals suggest numerous solutions, products, or ideas, and companies struggle to find innovative contributions within these data masses (Zhao and Zhu 2014). Given the data volume, manual identification of such innovations is neither feasible nor efficient. Effective identification becomes a challenge with these communities' vast and unstructured nature of data. Traditional, manual approaches like pyramiding or screening, while suitable in controlled settings, are not equipped to handle the vastness and dynamism of online communities (Hippel et al. 2009; Stockstrom et al. 2016). Therefore, identifying innovations from these online posts can be likened to harnessing the potential of crowdsourcing at scale, with potential benefits such as reduced innovation lead times, diversified solution pathways, and insights into user-driven market demands (Zhao and Zhu 2014). Thus, systematically identifying such innovative users and their ideas has increasingly gained attention in innovation research (Hippel et al. 2009; Kratzer et al. 2016; Lüthje and Herstatt 2004; Stockstrom et al. 2016).

Therefore, this study seeks to explore a novel process model for automating innovation identification in online communities. To effectively analyze the available data and identify user innovations, researchers and practitioners need to find ways to filter this textual information at scale with as minimal manual effort as possible. Several studies have started to apply computer algorithms to analyze large amounts of data (Hippel and Cann 2021; Hippel and Kaulartz 2021). New advances in machine learning and natural language processing enable researchers to analyze textual data and its meaning better. Hippel and Kaulartz (2021) recently introduced an approach that helps identify innovative users and posts by analyzing millions of online community texts. However, this approach still needs manual processing steps that could hinder scaling and yield potential human errors. Further, the authors call for using more advanced machine learning models. Building on their work, we seek to build a process model that requires minimal manual work.

Reducing the manual effort bears not only advantages in efficiency but also offers a consistent, scalable, and timely solution. Nevertheless, current research lacks an applicable process model to identify innovative ideas. A potential explanation is the missing training data: While online communities can be vast, the specific instances of genuinely innovative ideas might be sparse. Constructing a robust training dataset with labeled examples of innovative ideas can be challenging. Deep transfer learning, an advanced subfield of machine learning, has been increasingly recognized for its capacity to reuse pre-trained models from one task as the starting point for another (Pan and Yang 2010). This technique leverages learned features and parameters from an initial problem to enhance performance on a related but distinct task by relaxing the distribution requirements (Tan et al. 2018). Often utilized in scenarios with limited data, it can be a pivotal method to enhance deep learning model efficacy. Different online communities might have varied linguistic styles or nuances. However, the foundational textual structures remain consistent. By relying on hierarchical feature recognition, transfer learning ensures that a model trained on one community can be adapted to other communities with relatively minor adjustments. This adaptability ensures scalability, enabling the identification of innovations across diverse online platforms and communities without training entirely new models for each.

We follow the call of Hippel and Kaulartz (2021) and apply advanced natural language processing tools to identify lead users in online communities and outperform the dominant methods of innovation detection in rich textual data. In particular, we use BERT (Bi-directional Encoder Representations from Transformers) (Devlin et al. 2018), a state-of-the-art transformer-based machine learning model that helps to abstract the content of unstructured textual data better (Devlin et al. 2018; Vaswani et al. 2017). We utilized a transfer learning approach that trains on already labeled data and transfers the resulting model to a similar but different use case. For this study, we train a model to classify posts from a maker community and texts from various common online sources. Our resulting dataset contains 47,839 posts, including 23,920 on hackaday.io and 23,919 on Reddit, snippets of New York Times articles, and Amazon product ratings. Hackaday.io is a popular maker platform (Browder et al. 2019) that prior household sector innovation research has already investigated (Resch and Kock 2021). Users publish their projects on the platform by describing how they built prototypes and what motivated them. Our transformer-based A.I. model had the training objective of differentiating these maker posts from the diverse set of other texts. Subsequently, we transferred the trained model to identify potential user innovations. Building on prior user innovation research (Franke et al. 2006), we chose the context of kitesurfing to investigate user innovations. Thus, we crawled 1,010,545 posts from the popular kiteforum.com online community to apply and test our fine-tuned model.

The initial training achieved a 92.3% accuracy in classifying whether a post is from hackaday.io. Applying this trained model to the kite forum data resulted in classifying 8068 (0.8%) as potential user innovations. Subsequently, we manually validated the model's performance on a subsample and found an accuracy of 97.8%. Further, applying the model increased the share of user innovations from approximately 1% to over 50%, although the model was not initially trained in this context. The results also emphasize the need-expressing and prototype-building textual components in the posts.

Our findings contribute to the user innovation literature in four ways by introducing a new advanced approach to identifying user innovations effectively. First, we demonstrate that transfer learning can identify user innovations in online communities and thus helps minimize manual work for such machine learning methods without requiring manual coding and filtering steps. Second, building on prior work (Hippel and Cann 2021; Hippel and Kaulartz 2021), our process model further improves the model's results by applying state-of-the-art natural language processing techniques. Third, minimized manual work and improved results increase the accessibility of machine learning methods in the user innovation domain and adjacent research. Researchers can more easily integrate machine learning to identify user innovations at scale. Similarly, such tools reduce decision makers' underestimation of user innovations (Bradonjic et al. 2019). Fourth, our results show how machine learning techniques (i.e., artificial neural networks) enable deeper insights and potentially reveal new or enhance existing theories (He et al. 2020; Shrestha et al. 2020). Overall, this study's approach adds to a growing portfolio of methods that will build a toolset for future researchers and studies to approach the potentials and challenges of the ever-growing data from users and online communities.

Theory

User Innovation

Firms experience a growing pressure to develop innovations fast to stay competitive. Shorter product lifecycles and longer development increase this pressure. At the same time, anticipating market trends and future customer demands is inherently difficult for firms as information about needs is sticky (Hippel 1994). However, information about needs and solutions is fundamental as innovations constitute need-solution pairs (Hippel and Krogh 2015). While firms act as producers and often have the capability of finding a solution to a need, the knowledge about needs sticks to the users of products (Hippel 1994; Lüthje et al. 2005). As a result, some needs are unmet, leading users—users ahead of a trend who expect high benefits from a solution—to innovate solutions for their needs (Hippel 1986; Urban and Hippel 1988). While information stickiness hinders producers from finding proper need-solution-pairs, increasing access to information, new technologies, and tools (e.g., 3-D printers) further reduces the entry barriers for individuals to become producers and solve their needs (Baldwin and Hippel 2011).

This phenomenon in which private individuals spend their spare time to innovate is popular and yields advantages for firms seeking external knowledge since users' innovations show commercial attractiveness (Franke et al. 2006; Hippel 2006; Jong et al. 2021). Users can also outperform professionals when designing new products (Pollok et al. 2021). In addition to their commercial attractiveness, users innovate across all domains. In the U.K., household sector innovators spend more than 1.4 times more on their ideas than all consumer product firms in the U.K. combined (Hippel et al. 2012). Typically developed innovations by users are consumer goods across domains (Jong et al. 2015), extreme sports equipment (Franke and Shah 2003; Lüthje et al. 2005), services (Oliveira and Hippel 2011), software (Krogh and Hippel 2006; Lakhani and Hippel 2003), scientific instruments (Riggs and Hippel 1994), and even medical applications (Habicht et al. 2012; Kanstrup et al. 2015). In particular, user innovations pushed forward the field of extreme sports, and entire industries and niche markets emerged. Prominent examples include kitesurfing

(Franke et al. 2006; Hippel and Kaulartz 2021), kayaking (Baldwin et al. 2006; Hienerth et al. 2014), canyoning (Franke and Shah 2003), and mountain biking (Lüthje et al. 2005) that all have their roots in pioneering inventions by users to fulfill their own needs. With these pioneering need-solution pairs, users also become entrepreneurs and sell their solutions to others with the same need. For instance, the famous shoe firm On-Running was co-founded by a former professional athlete experimenting with garden hose pieces underneath shoes to fulfill previously unmet needs (On-Running). While initially intended to solve solely own needs, individual user innovations might address the needs of many others. Thus, the household sector innovation phenomenon holds significant potential advantages for firms seeking knowledge outside their boundaries (Afuah and Tucci 2012; Lilien et al. 2002) and for society (Gambardella et al. 2016).

User Innovation in Online Communities

Users not only innovate for themselves but also engage in open-source projects (Krogh and Hippel 2006), freely reveal their solutions (Krogh and Hippel 2006), collaborate to solve problems (Lakhani and Wolf 2003), and ultimately become more efficient in online communities than producers (Hienerth et al. 2014). The motivation for engaging in such collaborative innovation processes is not limited to solving personal needs. Instead, the participation is also self-rewarding and includes an intrinsic desire to learn, gain a reputation in the community, connect to like-minded individuals, or ultimately become an entrepreneur (Hippel 2017; Lakhani and Wolf 2003; Shah and Tripsas 2007). As a result, users exchange information and innovations as active members of online communities.

The value of online communities arises from their characteristic to facilitate knowledge flows between community members and sharing ideas (Faraj et al. 2011). Freely revealed knowledge and ideas enable individuals to build on others' work and create remixes (Stanko 2016). This information exchange and revealing starts a reinforcing cycle since knowledge about community members' needs and solutions becomes more accessible, which in turn lowers the complexity and increases the speed of developing solutions by building on previously shared ideas (Flath et al. 2017; Oehlberg et al. 2015; Stanko 2016; Voigt 2018). While opportunistic behavior to exploit these voluntary contributions could hamper the reinforcing cycle, online communities independently develop governance structures and protect freely revealed intellectual property through norms in the community (Bauer et al. 2016; He et al. 2020; O'mahony and Ferraro 2007). Thus, online communities provide a self-organized and accessible space for individuals to share needs and solutions that serve as potential commercial value for firms (Fisher 2019).

User innovators play an active and essential role in the innovative potential of online communities. As household sector innovators and hobbyists, individuals are likelier to share information. Especially lead users show innovative behavior and contribute knowledge in online communities (Jeppesen and Frederiksen 2006; Jeppesen and Laursen 2009). Lead users stand out by providing solutions through their technical expertise in addition to mentioning problems and needs (Mahr and Lievens 2012). The resulting solutions comprise commercially attractive innovations recognizable by other community members who then provide positive feedback (Jensen et al. 2014).

Not surprisingly, companies try to facilitate the ideas and information of innovative users. Not limited to, but especially crowdsourcing communities became a standard approach to engage with promising users (Zhao and Zhu 2014). Either specific challenges or open calls for ideas lead to collaborative problem-solving between the community and the company. However, using online communities as sources of innovation is problematic for them. First, crowdsourcing can result in an overwhelming number of ideas (Zhao and Zhu 2014). Filtering through them manually to find ideas takes a lot of time and resources. Second, not all submitted ideas are of high quality or even feasible. The idea descriptions also differ in terms of elaboration. Companies need to differentiate between what's merely novel and genuinely innovative and implementable. Last, the discussions can evolve as users interact, discuss, and iterate on ideas. Tracking these evolutions to identify the most promising directions is an added complexity. Consequently, harvesting freely available unstructured data for valuable user innovations offers promising advantages for firms, but the identification challenges them simultaneously.

Identifying User Innovations

Over the last decades, scholars have developed different approaches to identify and work with promising individuals in the user innovation phenomenon. Traditional approaches to identify lead users include pyramiding and screening (Hippel et al. 2009; Stockstrom et al. 2016). Primarily, pyramiding constitutes an efficient lead user identification approach through personal references. However, both approaches seem to hardly apply to the amount of data available in a diverse set of online communities posted by sometimes anonymous individuals. Similarly, broadcasting problems to attract the right solvers (i.e., crowdsourcing) involves significant challenges, such as neglecting distant ideas with increasing suggestions (Piezunka and Dahlander 2015). In addition, researchers started to use internet-based data for approaches that do not rely on users' self-assessment, such as netnography (Belz and Baumbach 2010) and social network analysis (Kratzer et al. 2016), showing that being active in online communities and bridging different subgroups correlate with lead user characteristics. Further, analyzing textual posts provides additional information to identify innovative ideas of users in online communities (Resch and Kock 2021).

Recently, researchers approached the challenge of identifying user innovations with computer-aided methods and developed the first artificial intelligence approaches. Hippel and Kaulartz (2021) mine textual posts in kitesurfing online communities. Hippel and Cann (2021) apply natural language processing to filter posts in two online communities to investigate behavioral user innovations. Both papers follow a similar approach by using semantic word space models that map words into an n-dimensional space so that semantically similar words (e.g., queen and king or pasta and pizza) appear closer than semantically unrelated words (e.g., fries and printer). These models used an initial word list of innovative terms to filter large textual datasets of online posts. Subsequently, including feedback from experts improved the filtering process iteratively. Finally, both studies successfully identified user innovations from millions of user-written online posts (Hippel and Cann 2021; Hippel and Kaulartz 2021). However, the applied processes still include manual work that provides opportunities for further improvements, such as building a list of filter words, preprocessing textual data, or expert feedback. In sum, both papers open the field for exploring advanced natural language processing methods to automate and improve the identification of user innovations and, thus, lay the foundation for this and future work.

Methods

Process Model Development

This study aims to develop an approach that reduces manual work and improves performance in automatically identifying user innovations in written online posts. To achieve this goal, we apply and combine two machine-learning approaches. First, we apply transfer learning to avoid manual coding. Second, we use a state-of-the-art natural language processing and deep learning technique called transformer to improve filtering and classification results. We outline these two methods in more detail in the following.

Transfer Learning

We seek to solve the task of classifying user-written online posts as a user innovation. Classification is a common task in machine learning and can, for instance, be performed by supervised learning. A model (e.g., an artificial neural network) needs manually coded data as a training set to apply supervised learning. For instance, for training a machine learning model to classify images of dogs and cats, that model has to train on a previously labeled image dataset of dogs and cats. Manually coding online posts as user innovations to train a machine learning model is not feasible. The manual workload is too high, and the manifoldness of innovative descriptions makes a distinction difficult. Tan et al. (2018) propose transfer learning for such cases, and we followed their suggestion. Transfer learning is an approach that applies a learned skill or knowledge to a different but similar domain. Similar to supervised learning, transfer learning can be performed on previously labeled data. However, transfer learning does not train on the task of interest but a similar one. Subsequently, the trained model is assumed to be transferable to the actual task. For instance, instead of labeling images of real cats and dogs, a model could be trained to classify a similar task (e.g., dolls of cats and dogs) and then be transferred to classify images of real animals. Models are pre-trained on general tasks to understand language and can be fine-tuned to more specific tasks such as answering questions, summarization, or text classification (Devlin et al. 2018; Vaswani et al. 2017).

Blitzer et al. (2007) describe the following use case: The objective is to classify product reviews into positive or negative sentiments, but creating a proper training set is too expensive. Therefore, they point out the need for transfer learning. In such a case, we can train a model relying on some arbitrary product reviews to classify other problems. Consequently, research proposes multiple use cases like automation (e.g., for production) (Maschler and Weyrich 2021), healthcare (e.g., Chen et al. 2020), or NLP (Raffel et al. 2019). Following the example idea and applying transfer learning for classifying user-written online posts as a user innovation, we need a data set similar to our actual task but already labeled. We propose to construct a dataset of different data sources and distinct domains. These domains function as labels for the classification task. More specifically, we look for existing and publicly available datasets of diverse common online communications as data that do not represent user innovations. We argue that the maker movement offers unique characteristics for identifying user innovations.

Maker Movement

As part of the household sector innovation phenomenon, the maker movement is an excellent source for innovations and is becoming increasingly popular. This development is facilitated by more accessible information and prototyping technologies (i.e., 3D printers and electronic development boards). Individuals can easily modify existing products or quickly create new hardware innovations by building on existing knowledge and easy-to-use platforms. Individuals in the maker movement, called makers, are passionate about learning skills in rapid prototyping technologies, using these skills to create new products and share them with others (Anderson 2012; Dougherty 2012). These prototyping technologies allow makers to overcome further the barriers between users and producers in the paradigm shift from manufacturer-producers to user-producers (Baldwin and Hippel 2011). Makers do not necessarily have a clear goal when learning and tinkering. However, makers' abilities, such as exploration, iteration, and solution-related knowledge, build a foundation to search for a solution if they discover a need. Thus, exploring possibilities and learning new skills by participating in the maker movement increases the likelihood of developing need-solution pairs (Hippel and Krogh 2015) when encountering a need. Consequently, the maker movement shows a particular innovative potential that other studies point out (Browder et al. 2019; Halbinger 2018; Resch and Kock 2021; Svensson and Hartmann 2018). In physical makerspaces, the makers' innovation rate is eight to 35 times higher than the consumer innovation rate (Halbinger 2018). Makers also actively share their ideas and collaborate on them in dedicated maker online communities (Resch and Kock 2021). Consequently, the essence of user innovation in the maker movement lies in its community-based and real-world context. Makers freely reveal their ideas and thus publish a need-solution pair by describing what they developed for which purpose. Thus, the textual idea descriptions include essential characteristics for this study's purpose as they offer transparency toward need-solution pairs. The rich discussions with peers, often present in the intermediate stages of the innovation process, are essential to capture the nuances and intricacies tied to the early phases of user-led innovations. Not only do these discussions revolve around technological specifications, but they also delve into design challenges and collaborative problem-solving. In sum, we argue that learning to identify maker's idea descriptions from other internet texts is a suitable approximation for identifying user innovations in different domains.

Transformer-based Natural Language Processing

In recent years, the advances and wide accessibility of hardware for processing large artificial neural networks and the availability of big text datasets facilitated the development of advanced natural language processing methods, including deep artificial neural networks. In 2017, (Vaswani et al.) introduced a new approach called transformer that utilizes an artificial neural network architecture, enabling a model to abstract a word's meaning based on a long context sequence. Using self-attention, the model learns to weigh the importance of each context word to enrich a focal word's meaning. Words are represented in a vector space where the distance between vectors translates to more distant word meanings. However, due to the selective attention to context and the model size, transformers promise advantages for representing the meaning of words or sentences over word space models. After its initial publication, many researchers and organizations adopted the transformer approach and developed modified architectures to achieve state-of-the-art results across many natural language processing tasks, including answering questions, sentiment analysis, summarization, named entity recognition, text translation, text generation, and text classification (Devlin et al. 2018; Vaswani et al. 2017). Transformers are currently highly performing compared to other approaches, and software libraries or pre-trained models are frequently published by organizations, academia, and open-source software community members, making this technology and its latest advances easily accessible. Given the performance promises and accessibility, we use a transformer model for this study.

Process model

Combining the single techniques using transfer learning and transformer models to identify user innovations in online posts, we apply four steps outlined in the following. Table 1 also provides an overview of these four process steps: (1) choose a machine learning model, (2) construct the training data for fine-tuning, (3) fine-tune the machine learning model, and (4) transfer the trained model to an online user community.

Step	Description	Outcome
Step 1	**Choose a machine-learning model:** Identify a machine learning model suitable for transfer learning and constitutes a state-of-the-art natural language processing model. Google's BERT is highly popular, bidirectional, and achieves good results across domains.	Pre-trained BERT (base)
Step 2	**Construct a dataset for fine-tuning:** Identify datasets representing a similar learning task. Online posts in the maker movement likely include need-solution pair descriptions. Distinguishing maker texts from a diverse set of common internet texts should mimic the task of finding user innovations.	Two datasets as positive and negative examples of user innovations: Positive: 46,843 texts of hackaday.io Negative: 46,829 texts of diverse online communications
Step 3	**Train the machine-learning model:** Train on the objective to classify the two types of datasets (step 2). Split the data in a train and test dataset to analyze the performance.	92.3% accuracy on the test data distinguishing positive and negative texts.
Step 4	**Transfer to the specific use case:** Transfer the trained model (step 3) to the context of interest (kitesurfing), label texts with a user innovation probability, and choose a threshold to classify user innovations.	8,068 posts remain out of 1,010,545 original kite forum posts after applying a threshold of 0.95.

Table 1. Process Description.

First, we need to find a suitable machine-learning model for this specialized task. The hardware, time, and data constraints make training such models from scratch impractical, especially given our goal of minimizing implementation effort. Therefore, the use of a pre-trained model is essential. Various entities, such as academic researchers, commercial firms, and even individual contributors, publish their pre-trained models, a notable resource being huggingface.com. Among the array of choices, BERT (Bi-directional Encoder Representations from Transformers), developed by Google (Devlin et al. 2018), stands out for several reasons grounded in data characteristics and model capabilities. Unlike text generation models like OpenAI's GPT (Generative Pre-trained Transformer) (Radford et al. 2018), BERT is designed to pay attention to both preceding and succeeding words around a focal word. GPT, in contrast, uses an autoregressive approach that limits its context to preceding words when predicting a subsequent word. This limitation becomes significant when classifying entire online posts, where a model's understanding can benefit immensely from the context provided by the entire text sequence. Another advantage of using BERT lies in its architecture. Online posts in communities are typically rich in contextual relationships between words, requiring a model capable of understanding this complexity. BERT's Transformer architecture excels at capturing long-range dependencies between words, making it superior for our needs compared to simpler word space models. Additionally, we chose the base BERT version, which consists of 109,483,778 parameters in its artificial neural network, aligning with our design guideline to keep the implementation and replication barriers low. This choice does not compromise the model's performance; BERT's pre-training on a comprehensive text corpus, including books and English Wikipedia, allows it to be fine-tuned for specialized tasks like text classification without intensive preprocessing.

Second, as outlined above, we need different datasets to separate texts similar to user innovations from other texts to minimize manual work and avoid manual coding. Thus, we collected two datasets. For the first dataset, we selected publicly available datasets of common online texts that are likely not to contain a user innovation. We carefully selected diverse texts that differed in length or formality and had technical expressions and raised opinions. These include New York Times comments, Reddit posts, news articles, tech news, SMS spam, mail spam, clickbait spam, and reviews, and can be downloaded on the data science platform Kaggle.com. The second dataset, selected for its high probability of user innovation content, draws from the rich innovative context of the maker movement (Browder et al. 2019; Halbinger 2018; Resch and Kock 2021). More specifically, we collected our second dataset from hackaday.io, an online maker community for sharing personal hardware projects. Community members can share their projects and interact with each other on the platform with the aim of discussions and collaboration, reiterating the authenticity of the dataset in reflecting genuine user innovation. When sharing their projects, individuals can provide an idea description, instructions, and further idea details in dedicated text sections on the project profile page. We collected projects with more than three likes, nine words, and ten followers to filter for minimum quality. The resulting dataset for positive examples of user innovations consists of 47,073 textual posts divided into 19,041 project descriptions, 14,182 instructions, and 13,850 project details. Table 2 summarizes the two datasets for negative and positive examples of user innovations used for the initial fine-tuning transfer learning process. To address potential biases in the model, the first dataset was meticulously curated to reflect a text number and length distribution similar to the second dataset (refer to Table 2). Moreover, we restricted our datasets to English texts, ensuring consistency in linguistic patterns and idiomatic expressions.

Third, with these datasets and the split between makers' and ordinary texts, we fine-tune the pre-trained BERT model by training it with the objective of classifying and distinguishing between the two types of texts. In doing so, we added a final layer of two artificial neurons representing the two classes of 'maker text' and 'no maker text.' The artificial neural network's output is probabilities the model assigns for each choice, which add up to 1. Further, we used the original hyperparameters of the BERT paper for the training.

Fourth, we transfer the fine-tuned model to an online user community. We deem the context of kitesurfing as a suitable setting for applying and testing our fine-tuned model since prior research found user innovations and lead users in this domain (Franke et al. 2006); it has already been investigated with machine learning methods (Hippel and Kaulartz 2021). There are vivid online communities constantly producing more unstructured data that makes screening all data impossible for human evaluators. Thus, we crawled the entire online posts of the platform *kiteforum.com,* which was also part of prior studies (Franke et al. 2006; Hippel and Kaulartz 2021). The resulting dataset contained 1,010,545 forum posts between October 31, 2001, and August 10, 2020. Subsequently, we applied our fine-tuned BERT model and classified all posts. We chose a conservatively high threshold for the user innovation probability (see the results for more details). Finally, the model classified 8,068 (0.8%) of 1,010,545 posts as user innovation.

		Text length			
Data	**Number**	**Mean**	**SD**	**Min**	**Max**
Positive train data					
Hackaday.io project descriptions	18,876	100.465	58.233	10	330
Hackaday.io project details	13,785	473.082	713.431	10	13,757
Hackaday.io instructions	14,182	146.499	297.128	10	10,467
Total (positives)	46,843	224.058	451.361	10	13,757
Negative train data					
Product reviews	9223	150.781	143.059	1	2799
New York Times comments	3500	26.303	12.516	1	49
Reddit posts	16,170	273.335	140.737	1	2656
Tech news	7000	243.296	147.29	1	1886
SMS	747	31.037	7.903	2	55
Email spam	1499	225.903	346.296	1	3948
News articles	3950	949.202	663.665	2	16,536
Clickbait spam	4754	10.251	3.94	1	28
Total (negatives)	46,843	251.169	349.773	1	16,536

Table 2. Description of the Datasets to Train the Classification Model.

Results

Results of Transfer Learning

The results of our four process steps include the fine-tuning results after training the model to classify maker texts (step 3) and the results of transferring the model to the context of kitesurfing (step 4). For the fine-tuning step, we split the dataset into a train (80%) and test (20%) dataset, retaining the 50/50 split of the maker and non-maker texts. Consequently, the test dataset is unknown to the model and serves as an evaluation of the training performed on the training dataset. An arbitrary cut-off value of 0.95 yields a 92.3% accuracy in classifying whether a post is from hackaday.io or not. Table 4 summarizes the classification results of the test dataset.

The subsequent application of the fine-tuned model to the online kitesurfing community classified 8,068 online posts (0.8%) of 1,704 users as potential user innovations. For this classification, we chose a conservative cut-off value of 0.95. The closer a cut-off value is to 1, the more restrictive a model is. Thus, choosing a high cut-off value should reduce a false positive rate but could also increase a false negative rate. Figure 1 shows the density of the model output for all texts representing the user innovation probability. The model assigns low user innovation probabilities to most text, while a small peak at higher probability values suggests a minority of text indicating user innovations. The portion of classified user innovations lies in the range of other studies' results. For instance, Hippel and Cann (2021) found around 1% of posts as innovative, and Belz and Baumbach found that 3.6% of community members are innovative using netnography in online communities. In Table 3, we present exemplary posts that were classified as user innovation or not. These classification results and illustrations support our primary motivation and objective by successfully identifying user innovations using transfer learning, thus minimizing manual work and considering the context for this classification by applying state-of-the-art machine learning architectures.

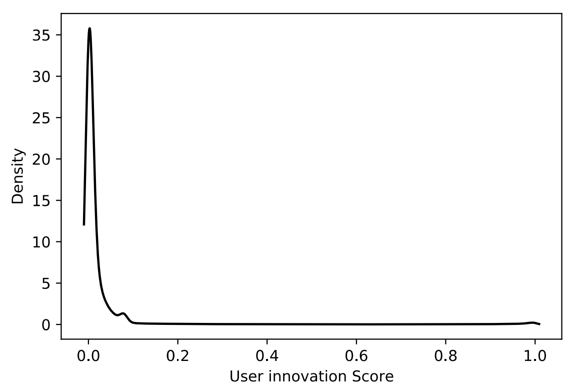

Figure 1. Density of the User Innovation Probability Outputted by the Fine-Tuned BERT model.

Post	**Classification**
(i) The *problem* with current quick-release systems is that the rider needs to operate them manually. However, when you are getting lofted by a sudden gust, there is no time to react manually. What is needed is a system that will operate automatically to depower the kite, an ideal system could operate during launching and landing times but be made inoperative out in open water to permit jumping, etc. *I* propose a system with a load cell tension sensor at the end of the kite line by the bar, the sensor would check line tension many times per second and feed the data to a system which could detect the "signature" of a dangerous event, such as a kite loop at launch time. For example, a load cell might put out an electronic signal proportional to the tension in the kite line. A cheap microprocessor with an analog-digital converter would convert the voltage signal into a digital signal, to be analysed inside the microprocessor. When a sustained pattern of voltage indicative of a "bad" event was output by the load cell, a pattern-matching program in	User innovation

the microprocessor would detect it. The microprocessor would then output a signal to a device which would depower the kite. One such device might be an electronically-driven cutting device attached to the kite line. An electronic signal would detonate a small incendiary charge that would either burn the kite line or force a small knife edge to cut the line.	
(ii) This would be a small, replaceable device, something like an electronically-activated firecracker. It could be shielded with plastic casing so that all the incendiary stuff happens safely inside a plastic tube placed somewhere along one of the kite lines. Of course, when a kite line is severed, the kite will depower, thus preventing the lofting. An alternative sensor system might also / or instead monitor pressure on the rider's feet [...] if the rider begins to lift off the ground, the pressure his heels exert on the ground would drop, and the safety mechanism could be triggered. The key is programming the pattern-matching device in the microprocessor. This could be done easily by operating a kite with load cells monitoring line tension, and recording the results as the kite is put through various maneuvers, preferably by an expert. The electronic patterns of various dangerous kite conditions could then be determined by examining the output of the sensors, which was recorded while the expert put the kite into these conditions. Anyone want to help build this device? *I can* do some of the microprocessor programming. There is a *commercial device* used by parachutists for auto deploying reserve chutes that might be adaptable for cutting kite line [...] the cypres auto release system. We could use that or *make our own* system [...] something like the electronic wire system used to ignite toy solid rocket motors could be adapted. The load cells would probably best be purchased from a *commercial* source [...]	User innovation
(iii) Arducopter has come a long way since *I* began using it and *I* believe it is a serious contender in the autopilot stakes. Since version 3, setup is a breeze and you should have no trouble flying right out of the box. Being open source, you have complete access to the code (*I have modified* parts of it myself). *I* use an external magnetometer (compass) alongside the ublox lea - 6h gps on a raised mount. *I* use the 3dr 433mhz radios or telemetry back to my android phone running droidplanner. Range 1km + my transmitter also receives telemetry data via the frsky transmitter/receiver fly with 2x8000mah 4s zippy lipo batteries. *I* use the turnigy mega 400W x2 charger and connected to the truck, can charge both batteries in 30min turnigy 9x transmitter which runs the er9x firmware and has been converted to use the frsky 2.4ghz transmitter module (which also has telemetry) range 2km + custom made carbon fiber gimbal using 2x gimbal brushless motor 4114 from ractime driven by the martinez controller. Fat shark attitude v2 5.8ghz - range approx. 500m take-off weight with GoPro: 5.85kg max static thrust 13.6kg (188a @ 15.5v) - measured in a custom-made testing rig) flight time: stable hover in no wind down to 14v (3.5v / cell) = 26min *I* have just today set up a dual operator system where a second operator.	User innovation
(iv) Yes, *I* completely agree. *I'm just finishing* up on my quick connect brackets for my efoil [...] so it attaches to almost all brands of foils, not the mast, but the fuselage with two hex / allen bolts so you can zip around, then unbolt, unplug, and go back out kitting or whatever you want.	User innovation
(v) *I* hook my leash above the chicken loop. Haven't had any *problems* with what you are describing.	No innovation
(vi) Have you tried the batwing? What gives you the basis for the "most stupid *invention*" claim? Doesn't sound like a very open mind.	No innovation
(vii) Just what *I* thought. It looks like an eleveight kite with zz north *prototype* printed on it.	No innovation
(viii) Exactly. *I* wonder how much longer it would take for the kite to move onto its wingtip at the edge of the window especially in light wind, because so many kites will just sit on their back and then just drift back to the middle of the window again. It seems to me that in those situations this "*innovation*" would make light wind water relaunch next to impossible.	No innovation
(ix) Hi Bruno, thank you for your *innovations* and sharing your thoughts with us on this forum. *I* have a 14m waroo and it just kind of sucks. Slow turning and poor through the turns. The wind range is good but that is about all... It's just not very fun to fly. Do you think that is just a *function* of the overall bow design not translating to high performance in the larger sizes (14m and up)? Does your new high aspect bow *prototype* address these issues and how? thanks Coleman	No innovation
(x) So you are light and intermediate and won't be riding serious waves. Buy a surfboard, just about any, thruster or quad, so long as it has a relatively flat rocker. Buy something you would ride in surfing, but with a bit less rocker or width. If you don't surf get your height +/- 2" and about 18" wide. Or your height - 4-6" if you want a fish. No expert, no need for $$$$ boards. No big waves or super high winds, no need for tiny or specialized shape. No racing, no need for extra speed (just don't get the hugest rocker). No huge airs, no fat ass = no need for carbon/epoxy. Want to learn strapless? Just get a surfboard! Should cost $300-600. Check it out and see if you like it. You can also use it to surf! If it breaks you can buy two more before you	No innovation

get to the aviso price point. Although theses fancy boards are all sweet, ask yourself, do you really need to spend >$1000 on a first surfboard, when you won't really surf it? If you are set on the options you mentioned, obviously the amundson seems most appropriate, unless you really need to drop a bankroll. If you lived at the beach and were hardcore, or gonna go to the beach a lot, move to H.I. or C.A., etc. maybe different advice, but that's my 2 cents' worth!!! meanwhile, let the pimping begin....	
(xi) Gopro on a kite can give a pretty cool perspective, especially if you're riding in a unique spot where you can't understand it unless you get that wide-angle overhead shot. Anyhow, *I* was *tinkering* with a new way of mounting a camera to my strut. *I* always used an iPod armband but was looking for something that would go on easier. Always a hassle trying to feed the velcro around the strut and then trying to tighten it. *I* decided to try a tube if 3"diameter polycarbonate. The wall is pretty thin, so not sure how it will work yet. what is cool is once *I* cut through it, the material springs in to form a smaller diameter. *I* don't see why this system couldn't work on a split strut system, haven't used this setup yet, but before *I* do *I* will line it with some rubber sheet to keep it from sliding and moving around.	No innovation (medium model score: 0.59)

Table 3. Exemplary User Innovation Classifications of kite forum posts by the transferred model.

Validation

Although the exemplary classification results of the online kitesurfing posts support our approach's objectives, these examples do not show if and to what extent our transfer learning approach improves the search for user innovations. Consequently, we validated the classification results by manually coding the online posts. In doing so, we first followed Hippel and Cann (2021) by randomly selecting 500 posts out of the 1,010,545 unfiltered posts and 500 posts out of the 8,068 filtered posts. We further followed the process steps to classify whether a text contains a user innovation or not (Hippel and Cann 2021; Jong 2016). We classified each post according to four main criteria: Was there an inventive step? Does the post not point toward a job-related/ professional invention? Is it an already existing product or behavior applied in the market? Does the idea solve a personal need? Two coders independently coded 1,000 posts with a strong rater agreement (k = 0.80) calculated by Cohen's Kappa (McHugh 2012). The manual coding found 11 out of the 500 unfiltered texts (2,2%) to contain user innovations while coding 281 out of the 500 filtered texts (56.2%) as user innovations. Thus, our model can identify user innovation over 25 times more likely than randomly selecting an online post. Comparing these improvements to Hippel and Cann's (2021) study, in which the likelihood of drawing a user innovation increased from 1% to 10% after applying machine learning, also suggests that the use of transfer learning and transformer models is not only suitable for identifying user innovations while minimizing manual work but also achieves new state-of-the-art results for automatically identifying user innovations.

The manual validation further enables a more detailed performance analysis of our machine learning model. Similar to the fine-tuning results, we analyzed the machine learning model's accuracy by comparing the model's classification with the manual coding of the 500 unfiltered posts. Table 4 shows the results of this comparison. The machine learning model correctly classifies 97.8% (true positives and true negatives). Due to a high cut-off value, the incorrectly classified posts mainly fall into the false negatives section. As a result, the machine learning model tends to sort out user innovations.

In addition to the quantitative analysis, the manual validation revealed detailed insights about the nature of users' community posts (as exemplified in Table 3). According to a summarizing classification of one coder, community members discuss a broad range of topics that include performing tricks, repairing, product reviews, purchasing advice, equipment, tips for beginners, weather forecasts, events, contests, sharing kite experiences, discussions about kiting places, traveling, community news, prototyping, tuning, inflating kites, measurement of kite statistics (i.e., speed or jump height), safety instructions, and injury reports. Remarkably, innovations take place in many of these topics and are not restricted to developing new hardware prototypes but also behavioral innovations (e.g., Table 3: i vs. iii). Our model was able to identify this diversity of different user innovation types in this study's context.

Table 3 highlights potential linguistics peculiarities an NLP approach can consider (italic). For example, first-person speech might indicate innovative activities as users focus more on their problems. Table 3 shows that it does not always express user needs and, thus, user innovation (Hippel and Cann 2021; Hippel and Kaulartz 2021). Community members mainly express their thoughts in first-person speech, no matter if they talk about their personal setup, technology, or user innovations. Similarly, innovation-related words such as prototype (vii), invention (vi), innovation (viii), commercial device (ii), or problem (v) do not necessarily imply user innovation but appear throughout all contributions. Interestingly, although not all posts are classified as user innovations, they often point towards need-solution pairs (viii, ix) (Hippel and Krogh 2015).

	Model classification	
	User innovation	No Innovation
Manually coded: User innovation	2	9
Manually coded: No innovation	2	487

Table 4. Results of Manual Validating the Model Outputs.

Discussion

In this paper, we aimed to develop an advanced process model to identify user innovations from online posts with minimal manual work. Many recent studies emphasize the potential for innovations arising from online communities (Dahlander and Frederiksen 2011; Faraj et al. 2011; Fisher 2019; Krogh and Hippel 2006; Safadi et al. 2021). Often, community members express these innovations in their textual communication. As part of the household sector, these individuals innovate to solve their own needs and ultimately freely reveal their ideas (Hippel 2017; Jong et al. 2021). Given this potential of free innovation and commercial attractiveness, scholars developed approaches to identify attractive users (Franke et al. 2006; Hippel et al. 2009; Stockstrom et al. 2016). However, traditional approaches such as manual screening or pyramiding are not applicable to the amounts of available data. Consequently, as a pioneering step, recent studies show how artificial intelligence can help to filter and automatically identify user innovation from written online posts (Hippel and Cann 2021; Hippel and Kaulartz 2021). Building on these advances, we presented an approach that further increases the quality of automated identification of user innovation while minimizing manual work.

Our proposed process combines two machine learning techniques. First, to analyze the text, we used a state-of-the-art machine learning architecture called transformer (Devlin et al. 2018; Vaswani et al. 2017). Second, we took advantage of transfer learning to train the machine learning model and minimize the manual work. These two process steps allowed us to reduce the manual work as it does not require manual labeling or repeated filtering loops. Instead, before applying the model, it is trained on data similar to the task of interest and is already labeled. The manual validation of the model's results showed that this transfer learning procedure can be applied to identifying user innovation. Further, using state-of-the-art machine learning architectures for text analysis, the identification results also improved as the whole context of texts is considered.

However, the ability to screen and filter large datasets automatically to identify user innovations does not result in substituting traditional approaches to use and integrate users and their innovations. Instead, we see these methodological advancements and traditional approaches as a complement. While filtering potential innovations can support inspiration, provide an overview, and sometimes already lead to innovations, traditional approaches such as the lead user method are valuable and necessary to integrate potential lead users (Lüthje and Herstatt 2004). Similarly, our process can serve as an initial search that will subsequently complement pyramiding (Hippel et al. 2009; Stockstrom et al. 2016). Using automated systems could even ensure a certain diversity of topics from which traditional approaches continue. Thus, machine learning approaches could support the efficiency and effectiveness of the search for valuable external knowledge and user innovations.

Theoretical Implications

With the presented results, our study contributes to the literature on user innovation and, more specifically, on its identification. First, our study substantially enhances the practicality and efficiency of identifying user innovations through automation. By leveraging transfer learning, we answer a critical need in the growing field of user innovation—the need for scalable, high-quality analysis. Existing manual methods are increasingly untenable due to the exploding volume of user-generated content online. However, advanced technologies require expert knowledge, and feedback loops or manual adaptations in stepwise filter processes are time-consuming. Our automated approach not only mitigates the need for manual oversight but also employs a pre-trained model that reduces the complexity involved in the analysis. This shifts the paradigm from labor-intensive methods to streamlined, automated systems, effectively democratizing the identification of user innovation to those without deep technical expertise.

Second, our work responds to the call for more advanced analytical methods in studying user innovation. We directly answer Hippel and Kaulartz' (2021) demand for more advanced natural language processing methods, such as BERT, and develop on previous semantic models. We rise to this challenge, demonstrating that such advanced models significantly outperform their predecessors in accuracy (Hippel and Cann 2021). An improved accuracy reduces subsequent manual work, and the more robust models can serve as an automated tool to identify and understand user innovation with greater precision.

Third, our study presents a foundational tool that can be integrated across various research contexts. The robustness and scalability of our method offer novel opportunities for empirical studies in related fields. The approach does not require user interaction but relies on objective text data (Bradonjic et al. 2019). Using transfer learning allows for measuring and quantifying "user innovativeness," which can serve as a helpful variable in social science research. This measure extends the text-based analytics beyond lead-user identification to potentially revealing nuances in user interactions and social network structures (Kratzer et al. 2016). These automated approaches can advance research by analyzing users' online interaction and innovative behavior without interference. Research opportunities include recognizing conversation patterns and longitudinal user behavior studies in online communities. Such studies could reveal when and how users start showing lead user characteristics and how community characteristics serve as antecedents or enabling factors. Similarly, this approach could help understand how user innovations resonate in a community. We look forward to this promising research path and the new insights possible with such tools.

Fourth, our work opens the door to machine-learning-driven theory development, a largely unexplored avenue (Shrestha et al. 2020). Following the work of He et al. (2020), who applied machine learning for inductive theory building on dispute resolution in GitHub, our study provides the foundational steps for future research to delve into the 'black box' of machine learning models. For example, the nuances of model predictions, as illustrated in Table 3, hint at the importance of contextual understanding of, for example, innovation-related terms—suggesting fertile ground for new theoretical frameworks.

Practical Implications

Our study also offers implications for practitioners, including the increased scale of external search and an access point to user innovation. First, our study fundamentally changes the landscape of external idea sourcing by introducing a scalable, automated process. Traditionally, organizations have been limited by human bandwidth in examining and selecting external ideas for innovation, a practice highlighted by literature as critical for competitive advantage (Baldwin and Hippel 2011; Franke et al. 2006; Hienerth et al. 2014; Jensen et al. 2014). Our automated approach significantly widens this bottleneck. Not only does it allow for the screening of larger datasets, it also minimizes the human bias that can plague distant searches in, for example, crowdsourcing (Afuah and Tucci 2012; Piezunka and Dahlander 2015). We recommend a hybrid approach for optimal results: initial automated screening to handle volume and minimize biases, followed by human evaluators for nuanced judgments. This multi-step strategy has proven effective in related fields like radiology, where machine-human collaboration achieves the highest accuracy for analyzing pictures (Wu et al. 2020). Similarly, automated systems can either prefilter ideas before human evaluators make final decisions or display indicators to reduce potential human biases.

Second, the ease of implementation of our tool demystifies the application of advanced machine learning methods in organizational processes. Specifically, this study illustrates the easy accessibility to state-of-the-art machine learning methods to integrate the search for user innovations in an organization's innovation process. By democratizing access to sophisticated technologies, our system lowers barriers to the exploration of external user innovation, an area often overlooked but critical for organizational growth (Bradonjic et al. 2019). The availability of user-friendly machine learning tools for innovation sourcing can serve as a 'gateway' for organizations, fostering a more comprehensive understanding and valuation of user innovations. The system can be integrated into existing innovation management platforms or utilized as a standalone feature for departments seeking to become more innovation-centric.

Third, our study catalyzes organizational cultural change, particularly regarding user innovation attitudes. Often, decision-makers are unaware or skeptical of the value that user innovations can bring to an organization. Our tool can serve as tangible evidence of the breadth and quality of ideas outside conventional channels. By allowing for easier access to such innovations, the importance of this often-underestimated asset becomes increasingly hard to ignore. In sum, approaches such as the one described in this study constitute tools that enable practitioners to experience the potential of user innovation and to screen and receive information and ideas across domains.

Limitations and Future Research

Our study has limitations, which also suggest a potential for future studies. First, our research context and dataset affect our findings' generalizability. Although we used the pre-trained BERT model without fine-tuning it on our specific text corpus not to constrain the model to community-specific lingo, our approach can be biased towards content about technical prototyping. Such a technical focus could lead to less attention to other important user innovations, such as behavioral user innovations (Hippel and Cann 2021) or even innovations in the open-source software domain (Krogh and Hippel 2006; Lakhani and Hippel 2003). Our manual validation showed that the model also identified behavioral innovations such as tips for performing new tricks, using tools, prototyping guidance, or safety instructions. Still, the context selection of the fine-training dataset could influence a model's tendency for particular kinds of user innovation. We encourage future research to conduct additional studies that include different kinds of user innovations and compare the models' results. Similarly, the performance of different initial datasets to train the machine learning model, including data on behavioral user innovations or innovations in the open-source software domain, could be evaluated. This could lead to either generalizable models or different specific models that contextualize the nature of users and their innovations.

Second, in addition to the generalization, the transfer learning process inherently assumes that the initial training task is similar to the actual task. We argue that data from the maker movement represents an excellent source for finding user innovations. However, not all maker texts have to include user innovation characteristics; naturally, some ideas are newer than others (Resch and Kock 2021). Nevertheless, we consciously favored the advantages of the transfer learning approach with its described implications of minimal work and accessibility. Still, we see potential model improvements with even more selective training data. To achieve these improvements without losing the advantages of this study, we suggest that future studies start with a transfer learning approach and, subsequently, further improve the model's results with a constant feedback loop of manually labeled texts.

We encourage future studies to build on our process and develop other approaches to broaden the toolset for automated user identification. While we aimed to show the applicability of transfer learning for user innovation and its outperformance against existing approaches, we emphasize comparing different technical methods. The evaluation section of this study did not exhaustively compare the proposed method against a range of alternative solutions. Specifically, the method was not tested against state-of-the-art classical machine learning classifiers with or without a transfer learning mechanism or non-transformer-based deep learning benchmarks such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs).

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