Leveraging AI-based Decision Support for Opportunity Analysis

Wolfgang Groher, Friedrich-Wilhelm Rademacher & André Csillaghy

> *"What all of us have to do is to make sure we are using AI in a way that is for the benefit of humanity, not to the detriment of humanity."*
>
> Tim Cook
> CEO, Apple Inc.

The dynamics and speed of change in corporate environments have increased. At the front-end of innovation, firms are challenged to evaluate growing amounts of information within shorter time frames in order to stay competitive. Either they spend significant time on structured data analysis, at the risk of delayed market launch, or they follow their intuition, at the risk of not meeting market trends. Both scenarios constitute a significant risk for a firm's continued existence. Motivated by this, a conceptual model is presented in this paper that aims at remediating these risks. Grounded on design science methodology, it concentrates on previous assessments of innovation search fields. These innovation search fields assist in environmental scanning and lay the foundation for deciding which opportunities to pursue. The model applies a novel AI-based approach, which draws on natural language processing and information retrieval. To provide decision support, the approach includes market-, technology-, and firm-related criteria. This allows us to replace intuitive decision-making by fact-based considerations. In addition, an often-iterative approach for environmental scanning is replaced by a more straightforward process. Early testing of the conceptual model has shown results of increased quality and speed of decision-making. Further testing and feedback is still required to enhance and calibrate the AI-functionality. Applied in business environments, the approach can contribute to remediate fuzziness in early front-end activities, thus helping direct innovation managers to "do the right things".

Introduction

The dynamics and speed of change in corporate environments have increased. Firms today find themselves confronted with volatility, uncertainty, complexity, and ambiguity, classified under the title *VUCA*. This development has added to the difficulty of making right decisions. Firms are now challenged to evaluate growing amounts of information within a shorter period of time in order to stay competitive. Applied to innovation, decisions on which opportunities a firm wants to pursue must be taken fast (Gassmann & Schweitzer, 2014).

In this context, the early front-end activities of an innovation process draw our attention. Identifying opportunities and risks at an early stage, along with classifying, evaluating and interpreting them to make timely and well-founded decisions, are considered as key tasks of strategic innovation management (Gerpott, 2013). Thus, the innovation process does not start with gathering and developing ideas, but rather with defining search fields for localizing where to innovate. A strategic innovation search field (ISF) is described by trends affecting the firm, by technologies, or by customer needs, and serves as a starting point for idea generation (Durst & Durst, 2016). Based on this understanding, assessing ISFs is a combined task of opportunity identification and opportunity analysis during early stages of the innovation process, as defined by Koen et al. (2002). It concentrates on assessing whether or not the pursuit of an opportunity makes sense by consulting technological and market-related criteria, along with the business perspective (Cooper, 1996). Without defining ISFs, ideas are often not in line with market needs or actual requirements. In consequence, plenty of ideas are existent, but very few or none advance into realization (Durst & Durst, 2016). This points out the high relevance of assessing ISFs. However, in business practice this relevance is not yet reflected, and the reasons behind it need to be analyzed.

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Established process models for innovation management, such as the frequently cited stage-gate model of Cooper, commonly start off with idea generation. Upstream scanning of a firm's environment is partly recognized or presumed as part of a strategic definition. The amount of data to be consolidated, processed, analyzed, and interpreted rises with increased dynamics and complexity of a firm's environment. Considering the exponential growth rate of data, this calls for tailored IT-support. According to Spath et al. (2010), information provision is the key determinant in the innovation process. In business practices, Internet-based search engines are broadly used in this context, but receive critical feedback. This is due to the significant time-effort involved, low quality of search results, insufficient support in limiting the search, as well as poor presentation of results. Owing to these obstacles, firms spend up to 10 hours or more per week simply retrieving information. These findings illustrate that there is currently no adequate IT-support for these activities. The strength of IT lies in supporting well-structured processes. Little-structured, knowledge-intensive processes, in contrast, call for tailored AI-support.

In this context we refer to AI as "tools and technologies than can be combined in diverse ways to *sense, cognize* and *perform* with the ability to learn from experience and adapt over time" (Akerkar 2019: 3). Within the broad field of AI, the ability to *cognize* natural language is especially relevant for assessing ISFs. Natural language processing has also contributed to developing the area of information retrieval, which is fueled by the currently exponential growth rate of text data on the World Wide Web. Content and link analysis of web pages, text mining, extraction of specified information from documents, automatic classification, and personalized agents hunting for information of interest to a specific individual are some of the active areas associated with information retrieval today (Akerkar, 2019). With the available information far exceeding the limits of human imagination, the named areas are of high relevance for assessing ISFs.

The situation described above leads to our central research questions:

- *How can innovation search fields be evaluated in a way that stimulates the quality and efficiency of the innovation process?*

- *How can selected AI-functionality be applied to identify the innovation search field with the best fit to a particular firm?*

In this context, quality refers to selecting the innovation search field with the best fit to the company´s innovation strategy, while efficiency considers the time-effort spent for evaluating a search field.

The purpose of this paper is to develop a conceptual model to assess ISFs, grounded on the methodology of design science research (Hevner et al., 2004).

Current Understanding

Our research looks at the innovation process from an information management and processing perspective. This is in line with Brentani and Reid (2012), who state that the process for developing new market offerings in firms, at its core, is an information processing activity.

Through information processing activities, information about markets, technologies, and competitors is translated into designing new market offerings. Cooper (1996) refers specifically to information acquisition, and proficiency in handling it during the early innovation process as key to new product success. Brentani and Reid (2012) highlight the importance of quality and speed of information flow, each having an important, but different impact on a firm's performance. According to them, quality of information impacts the specific focus of the innovation process. This ensures the creation of superior products for the marketplace, leads to product or service advantage, and has a positive impact on the firm's overall financial performance. At the same time, speedy information flow can result in significant first mover advantage. This has been shown to positively affect the ability of a firm to achieve competitive edge. Thus, quality of information flow leads to product advantage, while speed is important for achieving competitive advantage.

Considering this, it is surprising that so far little research has been dedicated to this topic. This is reflected in the currently available methods and IT-tools for opportunity analysis and evaluation in the early phase of innovation, which we have analyzed. Findings from this literature can be summarized as follows:

Regarding methods, three types can be distinguished. The first type covers methods for customer research and the involvement of customers, especially lead users. The second type refers to the topic of idea management, and the third one to process methods, such as design thinking. All of these methods presume that the appropriate ISF has already been defined. They each facilitate a different approach to generating, enhancing, and revising ideas with the aim of identifying the right one for follow up.

IT-tools for the innovation process, referred to with the term *computer aided innovation* (CAI), can be assigned to four categories, reflecting the potential benefits (Hüsig & Kohn, 2009):

• Efficiency enhancing
• Effectiveness enhancing
• Competence enhancing
• Creativity enhancing

Functions which automate the generation of reports, documentation, or analysis increase the efficiency of the user and are assigned to the category of "efficiency enhancing". Tools with the potential to enhance decision making by improving quality, accuracy, and timeliness of the information provided describe the category "effectiveness enhancing". This category also includes visualizing information. So far, ISF analysis and evaluation is not assisted by these first two categories.

The category "competence enhancing" addresses the fact that the implemented knowledge of many CAI-supported methods enables less proficient users to apply more sophisticated methodology with less effort. Examples of this are the integration of customers into the early innovation phase, or co-operative innovation processes between several involved parties. Such tools presume that the ISF has already been determined and that required information is readily available. In that respect, this category comes close to the first category, "efficiency enhancing". The last category, "creativity enhancing", comprises all IT-supported creativity methods. Again, this assumes that the appropriate ISF has been identified in advance.

The review of existing IT-tools makes apparent that the assessment of ISFs is so far not adequately supported. Summarizing the findings by analyzing existing process models, methods, and IT tools for opportunity analysis and evaluation, leads to the conclusion that current research on innovation processes mainly focuses on defining *how to win*, whereas understanding *where to play* remains a critical weakness.

Theoretical Framework and Approach

Compared to the later stages, the front-end of innovation is characterized by a high degree of uncertainty concerning market and technology development. This is associated with the following key questions:

• Which social, political, and economic trends are relevant for the core business, or can be leveraged to develop new market offerings?

• Which technologies, or novel combinations of technologies, can stimulate customers and increase market demand?

Our approach is grounded on the view of Brentani and Reid (2012) that considers the innovation process as an information processing activity. Our model draws on research by Koen et al. (2001), which shows that strategy alignment is crucial for innovation success. According to this, we include the novelty of an ISF itself into our model. This enables us to assess its level of development and thereby match it with the timing strategy of a firm for market launch. Finally, we refer to the innovation architecture of Augsten et al. (2017), who view innovation search fields from a market and technology perspective, describing their mutual dependencies. Connected to this, we include existing competences within the firm into our model.

Consolidating these different research streams, we have developed a novel model, denoted *Front-End Engine* (FEE), which assists in evaluating ISFs (Figure 1). The applied approach is guided by the design science methodology (Hevner et al., 2004), which is recognized in information systems research. Hevner et al. note that, "In the design-science paradigm, knowledge and understanding of a problem domain and its solution are achieved in the building and application of the designed artifact" (2004: 75). The artifact resulting from our work represents a conceptual model for assessing ISFs, which is discussed in the following section.

Conceptual Model Design

Model structure
The backbone of our model is built on selected AI-technology, which is capable of performing the functionality of "cognizing" for natural language (as per definition of AI above on pg. 30). To be precise, we apply

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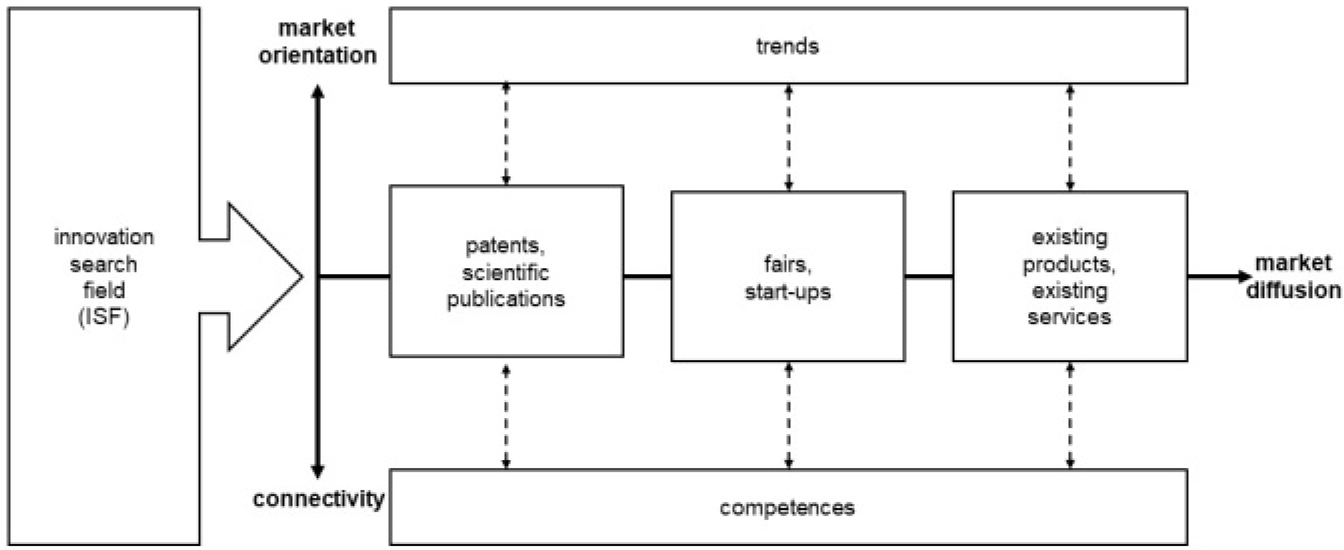

Figure 1. Structure of the Front-End Engine (FEE) model

information retrieval algorithms that capture semantic similarity between documents. After consulting the research of Thorleuchter and van den Poel (2013), we chose latent semantic indexing to proof the feasibility of the approach, based on knowledge that performance can be improved by using later approaches. Inside the model, documents are assigned to categories. Applying mutual reference of selected document categories, three different dimensions were analyzed.

The first dimension considers the time aspect by indicating **market maturity** of an ISF. The categories of patents, scientific publications, fairs, start-ups, and existing products and services each serve as a reference against which the ISF is compared. In the case that matches with patents or scientific publications dominate, an ISF is referred to as *pre-market*. At a later state, when relevance at industry and trade fairs or start-ups are detected, the ISF is rated as market entry. Finally, in the case of matches with existing products or services, it is characterized as *market domain*.

The second dimension captures the fit of an ISF with competencies and technologies that are available within the firm. We refer to this relation as **connectivity**. To allow for this, the model requires that competencies and technological assets of the firm are identified and described before evaluation starts.

Finally, the third dimension, **market orientation**, captures the conformity of an ISF with trends. Both connectivity and *market orientation* presume that market maturity has been determined, as they build upon their results. Those documents in each of the categories of patents, scientific publications, fairs, start-ups, and existing products and services, which show the best match with an ISF, form the basis for the subsequent comparison against competencies, as well as against trends.

Evaluation process

The FEE-objective is to substantially reduce the manual effort for evaluating an opportunity. Simultaneously high relevance and completeness of consulted documents need to be ensured.

As input for the evaluation process may serve multiple ISFs, which are generally the outcome of a moderated workshop. An ISF is typically described in one sentence and then enriched with associated functions and attributes. As a first step, the data base for each category is created. This is performed by means of vertical crawling using predefined entry points from the World Wide Web, as well as from firm-internal data sources. Each data source is assigned to one of the categories: patents, scientific journals, fairs, startups, existing products and services, or trends. In the following step, a semantic comparison of an ISF against the documents within each of the categories is performed. Subsequently, documents are ranked and shortlisted inside each category, according to the degree of matching. These shortlists are used to measure the characteristics for each of the three dimensions of the model. During the final step, results are consolidated

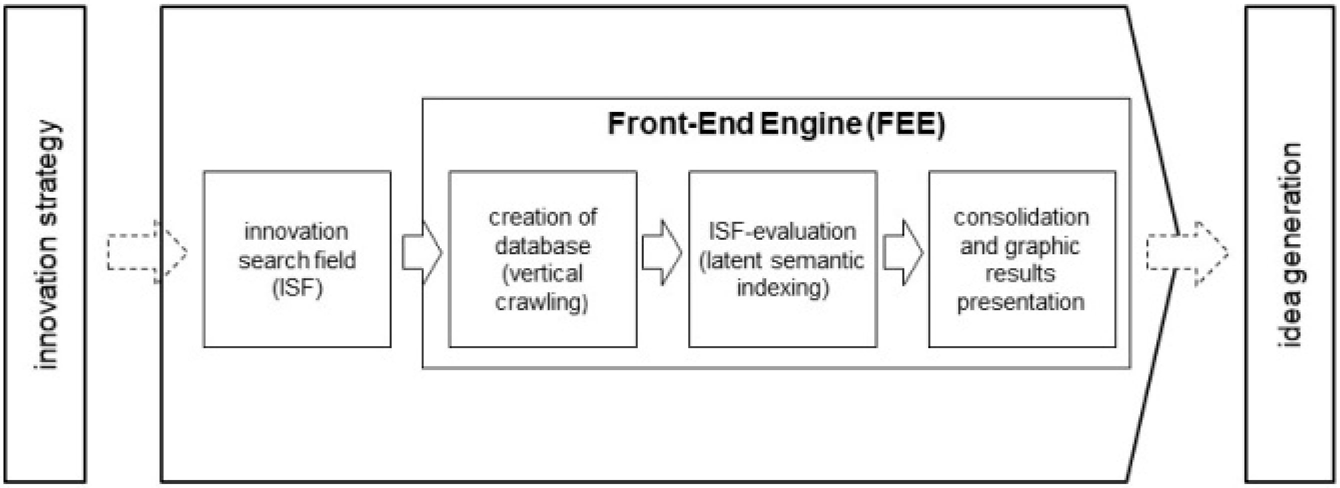

Figure 2. Process of ISF-evaluation

into a graphic results presentation. The corresponding process is shown in Figure 2.

Market maturity is captured on a nominal scale, differentiating the values *pre-market, market entry,* and *market domain*. Each value is associated with a characteristic search result profile, derived across all associated categories, except for trends, which are required in a later step. Market orientation and firm compatibility are both calculated as percentage values.

The chosen indicators enable a 3-dimensional interpretation of each ISF regarding conformance with timing strategy, firm-specific competences, and market orientation.

The novel aspect of this approach is that an often-iterative strategy for ISF-evaluation, if at all existent, is replaced by a more straightforward process. This is enabled by combining vertical crawling with semantic-based information retrieval. Specifically, latent semantic indexing (LSI) converts documents into a vector space, allowing for subsequent machine processing. By applying dimensionality reduction, the main topics covered in the documents can be grouped and extracted. The similarity between an ISF and identified topics can be determined based on distance measurement in the vector space. Search results are then grouped and listed in descending order. Finally, results are consolidated into a graphical results presentation. On that basis, multiple ISFs can be compared with a firm's particular innovation strategy to select the most appropriate one.

Findings and results

The FEE-approach was first elaborated in a research project (in the period from Nov. 2017 to Dec. 2018), sponsored by Innosuisse, the Swiss innovation agency. Project-internal tests and human-machine comparisons with industry users were successfully completed in Aug and Sep 2018. In a user lab setting, the FEE competed with two industry experts during the process step "creation of database" (Figure 2). The competition's scope was limited to the category of patents. The associated task was to identify documents online and select those with relevance for a chosen ISF. In this setting, and for two chosen ISFs, the test showed that the FEE can significantly reduce the required manual time effort. To reliably specify the FEE improvements, further testing needs to be conducted.

Furthermore, tests so far have revealed, that the original results list in each category, automatically created by the FEE, may need to be adjusted. This is because users may have various different perspectives in looking at an ISF. An industrial ISF can serve as an example to illustrate this. One user may restrict patent results exclusively to industrial applications, whereas another user might be interested in medical applications as well. Therefore, the FEE architecture adapts to this variance. It now allows leveraging the expert knowledge of the user, by offering the possibility of navigating within the results lists, and selecting a specific focus area. Based on the feedback of test users, this adjustment contributed to improving the quality of search results in a way that aligned to individual needs. Referring to the definition of AI in the introductory chapter, this added functionality provides the FEE with the ability to learn more specifically from user feedback, and thereby adapt to individual needs.

Another finding is that for technical documents, such as patents, the quality of search result tends to be higher than for colloquial texts, such as trends. The reason for this is that texts on technical patent topics consist of a higher chance of frequent co-occurring technical terms. As a result, a specific technical term occurs more frequently together with a paired term than expected (Thorleuchter & van den Poel, 2013). Both characteristics, the occurrence of characteristic terms and the frequent co-occurrences, enable researchers to identify more descriptive topics than can be realized by using only colloquial texts.

Limitations
Based on findings of our research so far, the developed conceptual model has proven to be capable of supporting the assessment of ISFs. Following a design science paradigm, the FEE currently requires further testing of all process steps in order to refine the conceptual model. Especially use cases from a broad range of industries should be conducted and reflected upon to enhance and calibrate the applied algorithms.

Practical relevance
The described results qualify the conceptual model as being applicable for practical use cases in the near future. Small firms especially can benefit, as little prior knowledge on how to assess ISFs is required, and the previous manual efforts required for environmental scanning are significantly reduced. As the FEE can adapt to user feedback, it has a positive impact on quality and speed of decision-making in the early front-end. The full benefit of the FEE can be reached in assessing and comparing multiple ISFs for a firm. In this scenario, intuitive decision-making can be replaced, or at least informed and supplemented by fact-based considerations. Hence, the described approach contributes to remediate fuzziness in firms' early front-end activities with a novel AI-based decision support, which serves to direct innovation managers to *do the right things*.

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