

6-18-2022

Towards a Generation of Artificially Intelligent Strategy Tools: The SWOT Bot

Christian Au
Mainz University of Applied Sciences, christian.au@hs-mainz.de

Till J. Winkler
University of Hagen, till.winkler@fernuni-hagen.de

Herbert Paul
Mainz University of Applied Sciences, herbert.paul@hs-mainz.de

Follow this and additional works at: https://aisel.aisnet.org/ecis2022_rip

Recommended Citation

Au, Christian; Winkler, Till J.; and Paul, Herbert, "Towards a Generation of Artificially Intelligent Strategy Tools: The SWOT Bot" (2022). *ECIS 2022 Research-in-Progress Papers*. 63.
https://aisel.aisnet.org/ecis2022_rip/63

This material is brought to you by the ECIS 2022 Proceedings at AIS Electronic Library (AISeL). It has been accepted for inclusion in ECIS 2022 Research-in-Progress Papers by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

TOWARDS A GENERATION OF ARTIFICIALLY INTELLIGENT STRATEGY TOOLS: THE SWOT BOT

Research in Progress

Christian Au, Mainz University of Applied Sciences, Mainz, Germany, christian.au@hs-mainz.de

Till J. Winkler, Hagen University, Hagen, Germany, till.winkler@fernuni-hagen.de and Copenhagen Business School, Frederiksberg, Denmark, winkler@cbs.dk

Herbert Paul, Mainz University of Applied Sciences, Mainz, Germany, herbert.paul@hs-mainz.de

Abstract

Strategy tools are widely used to inform the complex and unstructured decision making of firms. Although software has evolved to support strategy analysis, such digital strategy tools still require heavy manual work especially on the data input and processing levels, making their use time-intensive, costly, and susceptible to biases. This design research presents the ‘SWOT Bot’, a digital strategy tool that exploits recent advances in natural language processing (NLP) to perform a SWOT (strengths, weaknesses, opportunities, threats) analysis. Our artifact uses a feed reader, an NLP pipeline, and a visual interface to automatically extract information from a text corpus (e.g., analyst reports) and present it to the user. We argue that the SWOT Bot reduces time and adds objectivity to strategy analyses while allowing the human-in-the-loop to focus on value-adding tasks. Besides providing a functioning prototype, our work provides three general design principles for the development of next-generation digital strategy tools.

Keywords: Decision support systems, Strategy tools, Strategic analysis, SWOT, Natural language processing, Design science

1 Introduction

Strategy tools—such as a SWOT, Porter’s Five Forces, or the PEST model—are widely used among managers, analysts, and consultants in today’s business practice (e.g., Jarzabkowski and Kaplan, 2014; Wright et al., 2013; Vaara and Whittington, 2012 and or Clark, 1997). While the term ‘tool’ generally refers to anything that helps perform a specific task, *management tools* cover any model, concept, framework, method, or technique that helps to solve a managerial problem (Hakala and Vuorinen, 2020; Jarzabkowski and Kaplan, 2014; Knott, 2008). *Strategy tools* are a subset of management tools that deal with strategic challenges, such as understanding a company’s positioning and developing a new competitive strategy. Strategy tools are cognitive as well as material artifacts (Paroutis et al., 2015) that shape the mental models of strategists and hence affect both content and process of strategy work (Vuorinen et al., 2018). The application of strategy tools in practice is based on quantitative and qualitative inputs, where qualitative information seems to dominate.

Although the use of strategy tools has evolved from pen and paper drawings to digital templates and dedicated software suites over the past decades (Ain et al., 2019; Arnott et al., 2017), our initial analysis found that digital tools for strategy available on the market lack support on the input, processing, and output levels. Contemporary digital strategy tools heavily rely on human tasks because strategic analysis is a complex process that integrates knowledge and data from heterogeneous and often unstructured sources (Hakala and Vuorinen, 2020; Jarzabkowski and Kaplan, 2015). While human involvement in strategy processes matters (Reeves and Ueda, 2016), it also comes with certain costs (Grant, 2016).

There are substantial internal costs, e.g., for staff in strategy departments performing such knowledge integration tasks as well as external costs for strategy consultants (Paroutis et al., 2016; Gray, 2018). Albeit costly, the analysis through humans puts limits to the amount of available information that can be processed while at the same time making this process susceptible to human biases, such as confirmation biases (Nickerson, 1998).

The advent of artificially intelligent text processing through natural language processing (NLP) techniques, especially models based on the transformer architecture, promises new opportunities for decision support systems dealing with large amounts of unstructured data (Devlin et al. 2018; Wolf et al., 2020). This applies equally to strategy analysis, which is the problem domain we address in this research. We therefore pursue the question: *How can we increase efficiency, and reduce human bias, in the use of strategy tools?*

Taking a design science approach, we iteratively developed and prototyped the ‘SWOT Bot’, a digital strategy tool that automatically performs a SWOT (strengths, weaknesses, opportunities, threats) analysis. We argue that SWOT is a good instance for our problem domain since it is one of the most frequently used strategy tools in management (Jarzabkowski et al., 2009; Schneemann, 2019). Our design artefact consists of a feed reader (automatically retrieving, e.g., external analyst reports, annual reports, etc.), an NLP pipeline applying a pre-trained language model, and a visual interface aggregating and presenting the outputs.

Our development followed three design principles of (1) automatic data updates and signal extraction, (2) automatic synthesis of information, and (3) interactive data exploration and curation. Besides showcasing a functioning prototype in this paper, we argue these principles as generalizable to the development of next generation digital strategy tools, beyond our case of a SWOT. We believe a digital strategy tool such as our SWOT Bot will be of use particularly for corporate and business units that monitor competitor strategies on a regular basis as well as for consultancies that offer such strategic analyses as a service. A plan for the experimental evaluation of our design artifact with a sample of students and an evaluation in practice is provided.

2 Evolution and Design Requirements

Digital strategy tools can be related to broader classes of information systems (IS). They represent a class of decision support systems (DSS), because they focus on supporting and improving managerial decision making (Arnott and Pervan, 2016). They can also be seen as knowledge management systems (KMS) since they “... support and enhance ... processes of knowledge creation, storage/retrieval, transfer, and application” (Alavi and Leidner, 2001, p. 114). Digital strategy tools combine strategic management tools, that is abstract knowledge artifacts, with software and thus create digital material artifacts (Gregor and Jones, 2007). We use the input-processing-output model of software systems analysis (Boell and Cecez-Kecmanov, 2012) to display, based on our judgement, the degree to which components of past generations of (digital) strategy tools have been supported by technology. Figure 1 illustrates this evolution over the past decades. The nine common technical components of KMS are based on Shim (2002) and Saito (2007).

Traditionally, the application of strategy tools has relied on analogue material artifacts such as flipcharts, whiteboards, post-its and spreadsheets (Jarzabkowski et al., 2013). Since the rise of the desktop PC in the 1980s, practitioners have increasingly used Office software, such as Powerpoint and Excel, to document their results and conduct analyses (Kaplan, 2011). The focus of these tools has been to move from paper to digital files for the authoring and storing of the results.

Around the mid 1990s, multiple commercial vendors started to offer templates to implement specific strategy tools in these office applications. These Excel- and Powerpoint-templates not only help users document the results, but also present them in visually appealing ways and share them with others. Some templates embed the tool in workflows that allow to re-use the results at later stages for further analyses (e.g., by linking content from several Excel sheets). In the last years, online whiteboard-tools have emerged that provide users with visual templates for analytic and creative tasks (e.g., Miro).

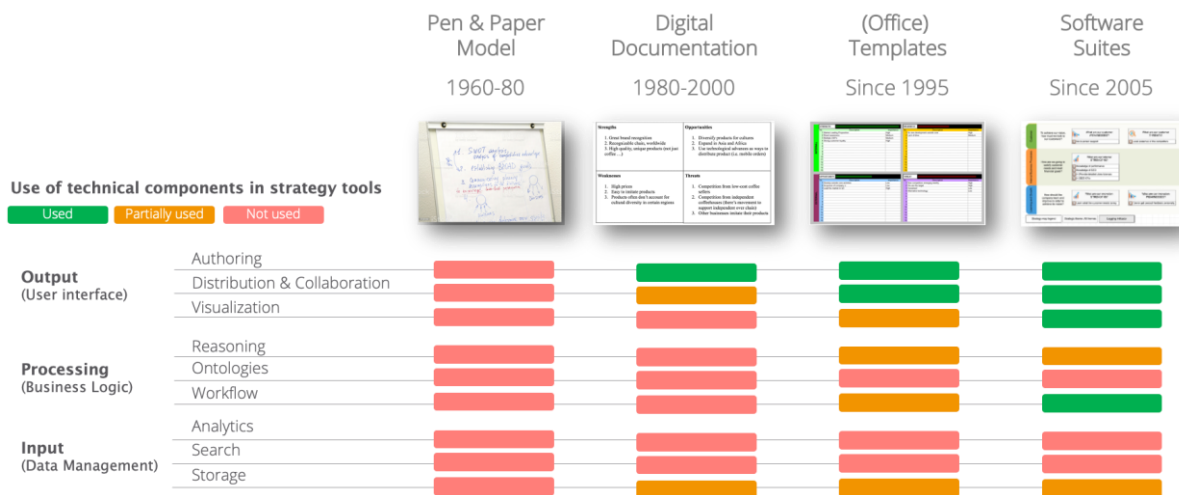


Figure 1. Evolution of digital strategy tools (authors' representation)

The latest generation of digital strategy tools are part of dedicated software suites, that not only document the results, but also support simple workflows. Some tools, for example, link strategy analysis to strategic planning by supporting the definition of key performance indicators, cascading them in the organization, and monitoring them. Due to their complexity, these tools are usually standalone applications (i.e., not built on top of Office applications). Most commercial tools focus on performance management issues, but there are some smaller vendors that offer software for the complete strategic planning process (i.e., from the design of vision and mission statements to environmental scanning).

Despite this evolution, the use of contemporary digital strategy tools comes with at least two important shortcomings. First, while they facilitate the visual representation on the output levels and offer some workflow supports on the processing level, they still require manual work to search, store and analyse primary information sources on the input and processing levels (see Figure 1). For example, a user performing a SWOT, PEST, or Five Forces analysis will typically search for information sources such as annual reports, external analyses, and news reports. The analysis of these information sources and their transformation into a synthesis of the dimensions of the specific strategy tool (e.g., the strengths, weaknesses, opportunities and threats of the SWOT) is a cognitive task that requires significant time and intellectual capability, depending also on the quantity and quality of the available sources and the experience of the analyst in performing this task.

Second, the cognitive processing, and the visualization or authoring on the output levels, inevitably introduce human biases due to the previous knowledge and individual interpretations of the analyst, such as confirmation biases (Nickerson, 1998). Confirmation biases are widely recognized as a tendency “...for people to seek information and cues that confirm the tentatively held hypothesis or belief, and not seek (or discount) those that support an opposite conclusion or belief” (Wickens and Hollands 2000, p. 312). Such biases can have multiple adverse effects in the domain of strategy analysis. Jarzabkowski and Kaplan (2015) point out that tool users have interpretive flexibility and tend to adapt the results according to their interpretations to support their favoured views. Phadermrod et al. (2019), for example, observed in brainstorming sessions that the SWOT analysis generated subjective judgements. Different interpretations can lead to different strategic conclusions, which pose a potential threat in strategy making (Fisher et al., 2020). While some level of interpretation, validation, and refinement through human involvement may be desirable, researchers have, in fact, ever since called for more objectivity in strategic decision-making processes. Hill and Westbrook (1997, p. 51) demanded for strategy practitioners an “... obligation to verify statements and opinions with data and analyses.”

In sum, while strategy tools have become more digitally supported over the past decades, the current generation of digital strategy tools falls short in assisting the analyst in the input and processing tasks, which in turn makes their work effortful and susceptible to human biases. Vuorinen et al. (2018) find that, until today, strategy work appears to have remained untouched by the technological developments

and the opportunities presented by crowdsourcing, big data analysis, and artificial intelligence. Against this backdrop, we put up three design requirements for next-generation digital strategy tools:

(1) Input: Digital strategy tools should support ***automated data updates and signal extraction***. This can be achieved through access to internal and external data sources with the help of APIs, automatic API-based data updates, collaborative identification and sharing of relevant information.

(2) Processing: Digital strategy tools should support ***automatic synthesis of information***. This involves the automatic extraction of relevant information in large texts, the synthesis or summarization of relevant text fragments, recognition of entities in the text and their ontological linkages.

(3) Output: Digital strategy tools should enable ***interactive data exploration and curation***. This allows users to understand complex information faster and trace relations between evidences. In addition, users should be able to quickly manipulate data points in order to add relevant information or overwrite algorithmic-based classifications and summarizations if these are inaccurate.

3 Design Science Approach

We followed a design science approach to address these three design requirements through a prototype artifact. Design science provides a methodological framework for problem-solving oriented research in IS that “... focuses on creating and evaluating innovative IT artifacts that enable organizations to address important information-related tasks” (Hevner et al. 2004, p. 98). We focused on the SWOT analysis since it is one of the most widely used tools in strategy analysis (Jarzabkowski et al., 2009; Schneemann, 2019). In addition, due to the moderate complexity of this tool with its four relatively intuitive dimensions, the SWOT provides a suitable example as a proof of concept. The development of our artifact, the SWOT Bot, was iterative and informed by theory (the knowledge base) and practice (the real world environment). It proceeded in three major stages.

The primary motivation can be traced back to the individual experiences of the authors of this paper—all of whom have backgrounds in strategy consulting—of how arduous, effortful, and at the same time imprecise the use of strategy tools is in practice. Based on this experience, one of the authors started building simple prototypes using structured data (e.g., from financial data providers such as Bloomberg and Factset) and the software Tableau. In a practice project with the market intelligence department of a large industrial company the authors learned, however, that the real pain for most analysts is the extraction of relevant insights from large amounts of qualitative data (such as news articles, annual reports, internal reports, etc.) rather than the evaluation of quantitative data.

Inspired by the idea to leverage natural language processing (NLP) for this problem, we evaluated, based on a small corpus of articles, which technology might work best for automatic summarization and information retrieval. We implemented a basic NLP pipeline to extract texts from documents, split them into smaller paragraphs and calculate sentence embeddings. We tested several models (specifically GPT-3 and roBERTa as BERT-derivate) with the help of standardized questions. Comparing the output of the models showed very encouraging results: 80% of answers extracted with roBERTa correctly identified by the model as crucial pieces of information from the articles. The manual extraction of information was performed by students.

In a third stage, we integrated the NLP pipeline and the models into a larger prototype and developed a front-end. Specifically, we built a news feed that would facilitate the retrieval of relevant data inputs based on key word search and connected this to the NLP component. The news feed is based on the App Feedly (2021) and allows configuring news streams based on press reports (filtered by keywords) or internal documents via RSS feeds. We also designed and implemented in collaboration with a UI expert a user interface that would allow business practitioners to quickly browse through extracted answers, to change the relevance assigned by the computer, and to add their own assessments.

4 Design Artifact: The SWOT Bot

We built a functional prototype to demonstrate the potential of NLP-supported digital strategy tools. Technically, the SWOT Bot leverages pre-trained transformer models to support analysts for question answering and topic clustering tasks. In following, we describe the three core components of the technical architecture of the SWOT Bot in more details, as displayed in Figure 2.

The Feed Reader

The *feed reader* allows analysts to receive a constant flow of events and news related to the topic they are planning to analyze. Analysts can easily configure a tailored news feed for a SWOT based on keywords (e.g., “BMW” or “automotive industry”) and specific news sources they consider relevant. Most media outlets provide an RSS feed that can be integrated in a feed reader to receive updates on articles published (e.g., the RSS feed of The Economist, 2022). The feed reader pushes new articles that are relevant to the feed. Users can browse their timeline to receive updates and bookmark articles they consider relevant easily. Articles that are highlighted by users are pushed to an RSS feed that forms the corpus of the SWOT and can be processed by the NLP pipeline. This can also be done cooperatively by multiple analysts.

There are plenty of existing commercial implementations of feed readers that can be used to configure a feed and receive updates. In our prototype, we use Feedly (2021), one of the most popular feed reader apps according to the download statistics of the Apples App Store and Android Play. Feedly provides both an API and an RSS feed, which we use to connect to the corpus created and retrieve the data for our NLP pipeline.

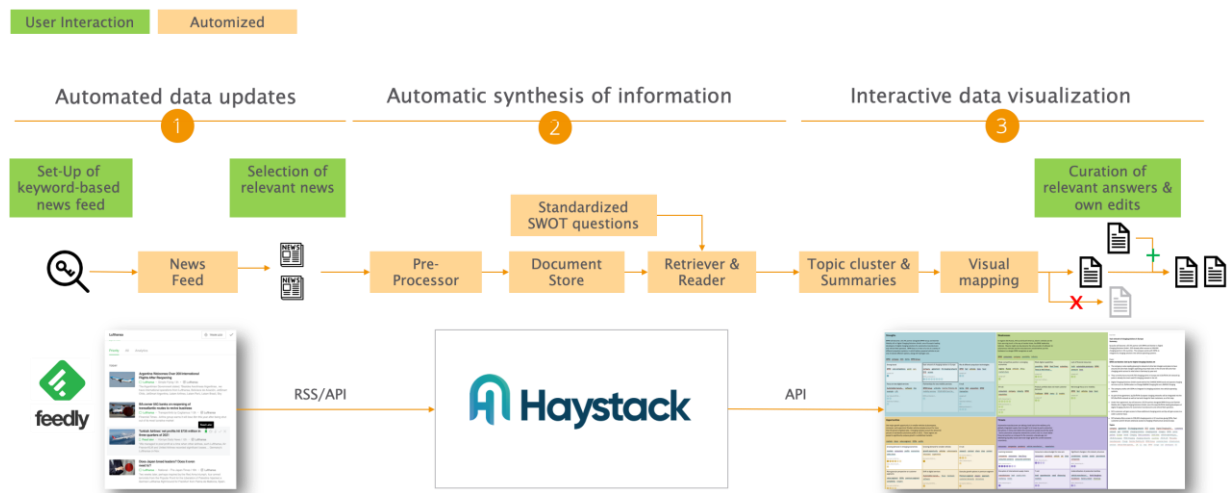


Figure 2. Software components of the SWOT Bot (authors’ representation)

NLP Pipeline

The corpus that analysts create with the help of the feed reader is used in a subsequent step as an input for the SWOT. The SWOT Bot automatically extracts the relevant information from the corpus by deploying an NLP model that is optimized towards question-answering-tasks. To this end, we use a BERT-based transformer architecture that builds on the latest advances in natural language technology (Wolf et al., 2020). Transformer-based pre-trained models are made available as open-source libraries by the research community and can be used to quickly build domain-specific applications. We specifically use roberta-base-squad2 as model for our tasks (Liu et al., 2019). RoBERTa is a BERT-based model that has been fine-tuned to the task of information retrieval in question-answering-systems.

It achieves state-of-the-art performance in the SQuAD 2.0 leaderboard that compares the accuracy of natural language models for reading comprehension tasks (cf. Rajpurkar et al., 2016). For the purpose of this prototype, we did not fine-tune Roberta to a specific language domain (such as strategy analysis). As future research, we plan to both train the language model to the strategy analysis domain and to the downstream task of question answering for SWOT-specific questions.

In our prototype we also use the platform Haystack Hub to store and pre-process documents with the help of roBERTa. Haystack is designed “... to be a very practical, down-to-earth open source NLP framework” (Haystack, 2021). It allows users to integrate several components relevant in a NLP pipeline from the pre-processing of documents, the implementation of a document-store and the usage of the latest transformer-based models such as roBERTa to retrieve information. Haystack Hub provides an API both to feed new documents in the document store as well as information-retrieval.

Our NLP pipeline works the following way: If a new document is highlighted in the feed reader the document is passed to a pre-processor which tokenizes the document and calculates sentence embeddings (for more details on how Transformer architectures work see Wolf et al., 2020). Resulting sentence embeddings are put in the document store. Relevant evidences from the new documents are extracted by passing standardized questions in the context of a SWOT to a reader-retriever component. The questions emulate an analyst, who wants to extract relevant information from documents. They are instantiated by filling variables X (company for which strengths and weaknesses) and Y (industry that is analyzed with respect to opportunities and threats). The questions are:

- “What are strengths of X, especially distinct capabilities and resources?”
- “What are X's weaknesses, specifically where does it have inferior capabilities or resources?”
- “What are opportunities for Y, especially trends that support demand?”
- “What are threats for Y, especially damaging trends?”

The reader returns a list of relevant answers for each question with a scoring that indicates the likelihood with which this a correct answer. All answers are stored in another database (implemented in Elasticsearch) in order to use them in the next step.

Weaknesses

- In regions like Russia, Africa and South America, electric vehicles are far from securing much in the way of market share, the BMW leadership believes . Waymo might one day become the only provider of software for autonomous vehicles and the manufacturers would deliver just the hardware is a danger BMW recognizes as well .

[BMW](#) [consumers](#) [company](#) [possibility](#) [industry](#)

Weak competitive position in emerging economies

[regions](#) [Russia](#) [vehicles](#)
[Africa](#) [market share](#)

spiegelL.pdf

Weak digital capabilities

[possibility](#) [BMW](#)
[Real Threat](#) [subsidiary](#)
[Tesla Is Well Ahead ...](#)

spiegelL.pdf

Tesla Has A Softwar...

Lack of financial resources

[truth](#)
[automobile producers](#)
[BMW](#) [pressure](#) [boss](#)

spiegelL.pdf

Weak digital capabilities Summary

BMW is taking part in the large-scale field test in California with just five vehicles, and Mercedes-Benz with only four . The average software content per D-segment, or large cars, stands at approximately \$1,220 or 10% of a car,ÄöVv's value .

From: [spiegel.pdf](#)

- BMW, on the other hand, is taking part in the large-scale field test in California with just five vehicles, and Mercedes-Benz with only four.
- The possibility that Waymo might one day become the only provider of software for autonomous vehicles and the manufacturers would deliver just the hardware is a danger BMW recognizes as well.
- The Real Threat. The only good news for the latter is that the Google subsidiary has no plans to build its own vehicles.

From: [Tesla Has A Software Business And It's Big.txt](#)

- 2.Tesla Is Well Ahead Of The Broader Industry In Terms Of Software Content Per Vehicle. Per an analysis by McKinsey, the average software content per D-segment, or large cars, stands at approximately \$1,220 or 10% of a car,ÄöVv's value .

Topics

[possibility](#) [BMW](#) [Real Threat](#) [subsidiary](#) [Tesla Is Well Ahead ...](#)
[hand](#) [Terms](#) [vehicles](#) [part](#) [field test](#) [Software Content](#) [Waymo](#)
[Vehicle](#) [manufacturers](#) [news](#) [latter](#) [California](#) [provider](#)
[Mercedes-Benz](#) [software](#) [software content](#) [analysis](#) [D-segment](#)
[Google](#) [10%](#) [McKinsey](#) [plans](#) [value](#) [car](#) [hardware](#) [cars](#) [vNv's](#)

Figure 3. Clustered answers under topics and summarization (Screenshot)

Dot-Connector

In the last step, all answers extracted automatically in the NLP pipeline are aggregated and presented to the user with the help of a visual interface, the Dot-Connector. Before the Dot-Connector visualizes the answers, it analyzes topics in the answers with the help of the sentence BERT architecture (SBERT).

SBERT is a modification of the BERT architecture. It achieves superior results in similarity comparison and clustering of documents compared to traditional BERT architectures by using siamese and triplet network structures (Reimers et al., 2020). Instead of classic clustering approaches, such as a latent Dirichlet allocation (LDA), which rely on bag-of-words models to cluster sentences (Blei et al., 2003), SBERT models allow us to calculate sentence embeddings for all evidences. Sentence embeddings consider the context of the words and thereby represent the meaning of sentences more accurately (Grootendorst, 2022).

Topics for the SWOT Bot are generated in three steps closely following the approach in Grootendorst (2022): First, for all evidences from the NLP pipeline sentence embeddings are calculated with the help of a state-of-the-art SBERT model (Hugging Face, 2022a). Second, the resulting embeddings are fed to an UMAP algorithm to reduce the dimensionality of the embeddings (McInnes et al., 2018) and subsequently clustered with the help of HDBSCAN (McInnes et al., 2017). Third, topic representations are generated by summarizing the clustered sentences with the help of the distilbart model, fine-tuned on the CNN news corpus (Hugging Face, 2022b). We also add named entities to each answer with the help of Google’s NLP API (Google Cloud, 2021).

The Dot-Connector is built in Svelte a Javascript framework. It presents for each dimension of a SWOT the following aspects, see Figure 3: (1) A summary of all answers identified, generated with the help of another fine-tuned transformer model (bart-large-CNN model developed by Facebook, see Hugging Face, 2022c), (2) Clusters of similar answers are identified and grouped together (using sBERT), and (3) all entities extracted from the answers. Analysts can use this interactive user interface to change the automatically assigned relevance of answers and sources in order to overwrite the relevance of answers calculated by the NLP pipeline.

5 Planned Evaluation

In line with the guidelines of Hevner et al. (2004) for design research, we plan to assess the SWOT Bot in terms of its utility, quality, and efficacy. We aim to do so in two stages, first in a controlled experiment with students and second through an evaluation in practice. The experiment (first stage) aims to test the time savings and the reduction of results biases through the use of the SWOT Bot. To this end, we plan to acquire part-time and full-time students in a Master-level strategy course. The subjects will be asked to develop a SWOT for two comparably complex company cases (e.g., two different automotive companies) in two separate runs. The text corpuses for each case will be provided. As tools, the subjects may use either (1) pen & paper or (2) the SWOT Bot and measure the times they need for this task. Since each subject assesses two company cases, we will assess whether the subjects were systematically faster using the SWOT Bot compared to using pen & paper.

	Group 1: Pen & paper	Group 2: SWOT Bot	
A. Control: No prior information given	A1	A2	Expected differences in the durations of the analyses
B. Treatment: Biased pre-information given	B1	B2	
	Expected differences in the assessments		

Table 1. Planned experimental design and group setup

In addition, half of each group will be manipulated through a bias (B: treatment groups) while the other half will not receive this bias (A: control groups). The bias will consist in the students reading a manipulated industry report (e.g., a text about the decline of the automotive industry) which is not part of the text corpus. This manipulated report plays down the strengths and opportunities and plays up the weaknesses and threats of the industry (or vice versa). After each run, the subjects will assess their individual analysis results in terms of the perceived degrees of strengths, weaknesses, opportunities and

threats of their company on given questionnaire scales. The comparison of these assessments between treatment (B) and control groups (A) will allow us to assess whether and to what extent the treatment groups were potentially biased by this (false) contextual knowledge. Our hypothesis is that the extent of this bias is larger between the pen & paper groups (A1, B1) and smaller between the SWOT Bot groups (A2, B2). Table 1 summarizes the planned experimental design and group split up.

In a second stage, we also plan to evaluate the SWOT Bot with a sample of expert practitioners, who work in strategy consultancies or strategy departments of larger firms and who are experienced in performing strategy analyses of companies. Analogous to the student groups, these subjects will be asked to perform a SWOT analysis on two comparable cases, one using pen & paper and the other using the SWOT Bot. Although the number of observations might not suffice for statistical analyses, we will measure the time for this task to estimate the relative time savings in practice. However, the focus of this second-stage evaluation will be on qualitative insights and the fit of our artifact for practice. To this end, we plan to interview the analysts before and after the use of the SWOT Bot and observe their work processes. Through the interviews, we hope to gain more insights into other potential advantages and disadvantages of our design artifact. For example, subjects might feel that the use of the artificially intelligent bot for the synthesis reduced their creativity and learning about the company case. We might also learn about the skills and training required for effectively using the tool from the interviewees. Or, they might provide additional clues where the synthesis of the bot has systematic omissions or shortcomings. In the spirit of an iterative artifact design in action (Sein et al., 2011), we thereby hope to gain additional insights for the further improvement of our design artifact.

6 Outlook and Future Research

We are confident to be able to present the evaluation results along with a live version of the prototype at the poster session of the ECIS 2022 conference in Timisoara. We hope to gain from the interaction with other conference participants inputs for the further development and dissemination of our work.

In our view, there are at least four promising avenues for future research emerging from our work that other researchers may find interesting to discuss with us. First, while we demonstrated the implementation of the three design requirements for a SWOT analysis and argued our approach to be applicable to other strategy tools, such as PEST or Porter's Five Forces, it will be necessary to expand the use of our artifact to other uses to underline its generalizability for qualitative strategy tools. Second, for all of these strategy tools, more labelled training data (e.g., company reports with labelled SWOT/PEST/Porter categories) should prove useful to fine-tune the automated synthesis and allow the language model to better learn the specific strategy analysis domain. Third, while the SWOT Bot is text-based, we see a potential for integrating number with text data to increase the quality of the results. Next-generation digital strategy tools could, for example, retrieve quantitative firm data from sources such as Bloomberg and Factset, in addition to our news feed, to bring more measurable indicators into the analysis. Fourth, group collaboration features could be included in artificially intelligent strategy tools such as our SWOT Bot to increase the value added in a collaborative work context.

In conclusion, while our prototype demonstrates that natural language processing has great potential within the context of digital strategy tools to support human analysis, more research is necessary to advance the knowledge in this field. We hope our work inspires other IS researchers to join this effort.

References

- Ain, N., Vaia, G., DeLone, W. H. and Waheed, M. (2019). "Two decades of research on business intelligence system adoption, utilization and success – A systematic literature review," *Decision Support Systems* 125, 113113.
- Alavi, M. and Leidner, D. E. (2001). "Knowledge management and knowledge management systems: Conceptual foundations and research issues," *MIS Quarterly* 25 (1), 107-136.
- Arnott, D. and Pervan, G. (2008). "Eight key issues for the decision support systems discipline," *Decision Support Systems* 44 (3), 657-672.

- Arnott, D. and Pervan, G. (2016). "A critical analysis of decision support systems research revisited: The rise of design science," in: Willcocks, L. P., Sauer, C. and Lacity M. C. (eds.) *Enacting Research Methods in Information Systems*, 43-103, London: Palgrave Macmillan.
- Arnott, D., Lizama, F. and Song, Y. (2017). "Patterns of business intelligence systems use in organizations," *Decision Support Systems* 97, 58-68.
- Blei, D. M., Ng, A. Y. and Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, 3 (Jan), 993–1022.
- Boell, S. and Cecez-Kecmanov, D. (2012). "Conceptualizing information systems: From 'Input-Processing-Output' devices to sociomaterial apparatuses," *European Conference on Information Systems (ECIS) 2012 Proceedings*. 20. URL: <https://aisel.aisnet.org/ecis2012/20> (visited on March 28, 2022).
- Burke, G. T. and Wolf, C. (2021). "The process affordances of strategy toolmaking when addressing wicked problems," *Journal of Management Studies* 58 (2), 359-388.
- Clark, D. (1997). "Strategic management tool usage: A comparative study," *Strategic Change* 6 (7), 417-427.
- Devlin, J., Chang, M.-W., Lee, K. and Toutanova, K. (2019). *Bert: Pre-training of deep bidirectional transformers for language understanding*. arXiv preprint. URL: <https://arxiv.org/abs/1810.04805> (visited on March 28, 2022).
- Feedly (2021). *Tracking feedback across the web without having to read everything*. URL: <https://feedly.com/> (visited on Mach 28, 2022).
- Fisher, G., Wisneski, J. E. and Bakker, R. M. (2020). *Strategy in 3D: Essential tools to diagnose, decide, and deliver*. Oxford: Oxford University Press.
- Haystack (2021). *deepset-ai/haystack*. URL: <https://github.com/deepset-ai/haystack/> (visited on March 28, 2022).
- Google Cloud (11.09.2021). *Cloud natural language. Analyzing entities*. URL: <https://cloud.google.com/natural-language/docs/analyzing-entities?hl=en>. (visited on March 28, 2022).
- Grant, R. M. (2016). *Contemporary strategy analysis*, 9th Edition. Chichester: John Wiley & Sons.
- Gray, J. (2018). "Boom time for Germany's management consultants," *Handelsblatt*. URL: <https://www.handelsblatt.com/english/companies/double-digit-growth-boom-time-for-germanys-management-consultants/23694984.html?ticket=ST-4284732-42ZYldmCgHYq3p111apL-cas01.example.org> (visited on March 28, 2022).
- Gregor, S. and Jones, D. (2007). "The anatomy of a design theory," *Journal of the Association for Information Systems* 8 (5), 312-335.
- Grootendorst, M. (2022). *BERTopic: Neural topic modeling with a class-based TF-IDF procedure*. arXiv preprint. URL: <https://arxiv.org/abs/2203.05794> (visited on March 28, 2022).
- Hakala, H. and Vuorinen, T. (2020). *Tools for Strategy: A starter kit for academics and practitioners*. Cambridge: Cambridge University Press.
- Hevner, A. R., March, S. T., Park, J. and Ram, S. (2004). "Design science in information systems research," *MIS Quarterly* 28 (1), 75-105.
- Hill, T. and Westbrook, R. (1997). "SWOT analysis: It's time for a product recall," *Long Range Planning* 30 (1), 46-52.
- Hugging Face (2022a). *all-mpnet-base-v2*. URL: <https://huggingface.co/sentence-transformers/all-mpnet-base-v2> (visited on March 28, 2022).
- Hugging Face (2022b). *sshleifer/distilbart-cnn-6-6*. URL: <https://huggingface.co/sshleifer/distilbart-cnn-6-6> (visited on March 28, 2022).
- Hugging Face (2022c). *facebook/bart-large-cnn*. URL: <https://huggingface.co/facebook/bart-large-cnn> (visited on March 28, 2022).
- Jarzabkowski, P. and Kaplan, S. (2015). "Strategy tools-in-use: A framework for understanding 'technologies of rationality' in practice," *Strategic Management Journal* 36 (4), 537-558.
- Jarzabkowski, P., Oliveira, B. and Giullietti, M. (2009). *Building a strategy toolkit: Lessons from business: Executive briefings*. London: Advanced Institute of Management Research.

- Jarzabkowski, P., Spee, A. P. and Smets, M. (2013). "Material artifacts: Practices for doing strategy with 'stuff'," *European Management Journal* 31 (1), 41-54.
- Kaplan, S. (2011). "Strategy and Powerpoint: an inquiry into the epistemic culture and machinery of strategy making," *Organization Science* 22 (2), 320-346.
- Knott, P. (2008). "Strategy tools: who really uses them?" *Journal of Business Strategy* 29 (5), 26-31.
- Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L. and Stoyanov, V. (2019). *Roberta: A robustly optimized bert pretraining approach*. arXiv preprint. URL: <https://arxiv.org/abs/1907.11692> (visited on November 15, 2021).
- McInnes, L., Healy, J. and Astels, S. (2017). hdbscan: Hierarchical density based clustering. *The Journal of Open Source Software* 2 (11), 205.
- McInnes, L., Healy, J., Saul, N. and Großberger, L. (2018). UMAP: Uniform Manifold Approximation and Projection. *Journal of Open Source Software* 3 (29).
- Nickerson, R. S. (1998). "Confirmation bias: A ubiquitous phenomenon in many guises," *Review of General Psychology* 2 (2), 175-220.
- Paroutis, S., Franco, L. A. and Papadopoulos, T. (2015). "Visual interactions with strategy tools: producing strategic knowledge in workshops: Visual interactions with strategy tools," *British Journal of Management* 26 (1), 48-66.
- Paroutis, S., Angwin, D. and Heracleous, L. T. (2016). *Practicing strategy: Text & cases*, 2nd Edition. Los Angeles: SAGE.
- Phadermrod, B., Crowder, R. M. and Wills, G. B. (2019). "Importance-Performance analysis based SWOT analysis," *International Journal of Information Management* 44, 194-203.
- Rajpurkar, P., Zhang, J., Lopyrev K. and Liang, P. (2016). *SQuAD: 100,000+ questions for machine comprehension of text*. URL: <https://arxiv.org/abs/1606.05250> (visited on March 28, 2022).
- Reeves, M. and Ueda, D. (2016). Designing the machines that will design strategy. *Harvard Business Review*. URL: <https://hbr.org/2016/04/welcoming-the-chief-strategy-robot> (visited on March 28, 2022).
- Reimers, N. and Gurevych, I. (2019). *Sentence-bert: Sentence embeddings using siamese bert-networks*. arXiv preprint. URL: <https://arxiv.org/abs/1908.10084> (visited on March 28, 2022).
- Saito A, Umemoto, K. and Ikeda, M. (2007). "Strategy-based ontology of knowledge management technologies," *Journal of Knowledge Management* 11 (1), 97-114.
- Schneemann, P. (2019). *Different perspectives on strategizing-theory and practical use of strategy tools*. PhD thesis, London Southbank University.
- Sein, M. K., Henfridsson, O., Purao, S., Rossi, M. and Lindgren, R. (2011). "Action design research," *MIS Quarterly* 35 (1), 37-56.
- Shim, J.P., Warkentin, M., Courtney, J. F., Power, D. J., Sharda, R. and Carlsson, C. (2002). "Past, present, and future of decision support technology," *Decision Support Systems* 33 (2), 111-126.
- Spee, A. P. and Jarzabkowski, P. (2009). "Strategy tools as boundary objects," *Strategic Organization* 7 (2), 223-232.
- The Economist (2022). *RSS Feed*. URL: <https://www.economist.com/rss> (visited on March 28, 2022).
- Vaara, E. and Whittington, R. (2012). "Strategy-as-Practice: Taking social practices seriously," *Academy of Management Annals* 6 (1), 285-336.
- Vuorinen, T., Hakala, H., Kohtamäki, M. and Uusitalo, K. (2018). "Mapping the landscape of strategy tools: A review on strategy tools published in leading journals within the past 25 years," *Long Range Planning* 51 (4), 586-605.
- Wickens, C. D. and Hollands, J. G. (2000). *Engineering Psychology and Human Performance*, 3rd Edition. Upper Saddle River, NJ: Prentice-Hall.
- Wolf, T., Chaumond, J., Debut, L., Sanh, V., Delangue, C., Moi, A., Cistac, P., Funtowicz, M., Davison, J., and Shleifer, S. (2020). "Transformers: State-of-the-art natural language processing," *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, 38-45.
- Wright, R. P., Paroutis, S. E. and Blettner, D. P. (2013). "How useful are the strategic tools we teach in Business Schools?" *Journal of Management Studies* 50 (1), 92-125.