

# Investigating Current Directions in Cross-Industry Innovation Research – a Systematic Literature Review

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## Research

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# Abstract

Background: The companies' operative environment is covered by a constant change through digitization, industry 4.0, artificial intelligence and megatrends, which pose enormous challenges. In order to master these challenges, the development of knowledge from foreign industries is a possible solution. This phenomenon is called cross-industry innovation. The aim of this study is to identify major directions in cross-industry innovation research. An essential part of science is to build on and enhance already published knowledge. In order to identify this knowledge and to offer a comprehensible and reproducible process, a systematic approach is required. For this study, a systematic literature review will be applied. During the review of the relevant literature, an understanding of the broad and deep nature of the literature emerges and it is possible to identify research gaps, which is often based on qualitative analyses. We will develop a new approach for analyzing literature based on semantic similarity analysis.

Methods: In order to achieve the research objectives a systematic literature review is applied and slightly modified. First, we will apply a systematic literature review protocol to establish reproducible results. Second, we develop a new approach for analyzing literature using a combination of semantic similarity analysis and a cluster analysis.

Conclusion: This review will aid in determining the directions of cross-industry innovation. Overall, six directions of cross-industry innovation research can be identified. Furthermore, this study offers a new approach for analyzing literature based on quantitative analysis like semantic similarity analysis.

## Background

The digital transformation is confronting economies with radical structural change. Existing value chains are being modified by new data, networking, automation and the digital customer interface [1]. Many of these technological challenges cannot be mastered with existing knowledge, known strategies and proven technologies. New solutions are needed, which require interdisciplinary developed innovative solution. The search for interdisciplinary solutions is connected to an opening of the innovation process. The open innovation paradigm elaborated by [2] states a shift from the traditional thinking of closed companies' innovation departments to a more open corporate innovation culture.

However, while we know a lot about the open innovation phenomenon described by [2], literature on open innovation primarily focus on "one-on-one relations between innovation partners" [3]. According to [3], researchers should address more complex settings of open innovation practices. [4] identifies the need for more complex settings of open innovation practices. They pursue the idea that the company's own innovation potential can be increased by involving distant knowledge source in the innovation process. [5] uses the term cross-industry innovation (CII) to describe the transfer of knowledge and solutions beyond industry boundaries based on analogical thinking.

CII is also gaining interest in industry. Since 2016, NASA has organized an annual "cross industry innovation summit" with topics related to CII [6]. A further conference took place 2018 in Hamburg, which

focused primarily on CII between the creative industry and public or semi-public institutions [7]. In addition to the interest of the business community in the context of conferences, an article in the management magazine Harvard Business Review also refers to the topic of CII [8]. Besides industry, science is also interested in CII. A Google Scholar search of the term “cross industry innovation” in the period between 1970 and 1999, which was conducted on 11th March 2019, leads to 12 results. The same search in the period between 2000 and 2018 leads to 872 results. This raises the question about the development of CII research. Surprisingly, no study is published which summarizes the CII research and presents its major directions. Therefore, this study sheds light on CII research and contribute a systematic literature review for an improved understanding of its origin and its state-of-the-art. This leads to this paper’s research question: What are the major directions in CII research?

The structure of this study is divided into six chapters. After the introduction in chapter 1, the methodological basics with the focus on the systematic literature review follow in chapter 2. In chapter 3, the systematic literature review is adapted and concretized for the case of the CII. Chapter 4 presents the results, which is followed by chapter 5 that introduces future research by the use of the morphological box method. Chapter 6 summarize the work of this study with a conclusion.

## Research Methodology

An essential part of science is to build on and enhance already published knowledge. In order to identify this knowledge and to offer a comprehensible and reproducible process, a systematic approach is required. For this study, a systematic literature review (SLR) is applied and adapted. During the review of the relevant literature, an under-standing of the broad and deep nature of the literature emerges and it is possible to identify research gaps [9]. In the following, according to [9] a SLR process is applied and slightly modified. [9] analyzes scientific articles on the methodology of literature review with the objective to develop a guidance of how to conduct a SLR. The process can be divided into the major steps “planning the review”, “searching and extracting literature” and “analyzing literature and reporting the review”. The three major steps comprise eight sub steps “formulate the problem”, “develop and validate the review protocol”, “search the literature”, “screen for inclusion”, “assess quality”, “extract data”, “analyze and synthesize data” and “report findings” (see Fig. 1).

insert Fig. 1 around here

The first major step “planning the review” comprises the sub steps “formulate the problem” and “develop and validate the review protocol”. First, it is important to become aware of the SLR’s goal and “formulate the problem” which requires determining re-search questions to customize the following research design. This is because the research design should be designed to answer the research questions [9].

Within the sub step “develop and validate the review protocol” a suitable research de-sign has to be developed and documented. The protocol allows a reproducible SLR, which improves the reliability. Furthermore, the protocol should include the research question, inclusion criteria, search strategies, quality assessment, data export strategy and reporting.

The second major step “searching and extracting literature” comprises the sub steps “search the literature”, “screen for inclusion”, “assess quality”, “extract data”. The major goal is to identify and collect the relevant articles and ensure the quality.

Within the sub step “search the literature” the literature search methods are determined. [10] proposes a backward and forward search. The backward search uses the references of an article as a starting point to get a list of potential articles. A research area can be explored in an iterative search for further topic related references [10]. In contrast to backward search, forward search considers the citing articles of a basic article. In an iterative forward search approach, it is possible to open up a research area [10]. Today’s literature databases (Scopus, Web of Science, and Google Scholar) are the primary way to search for literature. These databases can be searched based on keywords [11]. Different types of databases existing, each with a different scope.

In addition to the basic selection of the search strategy, detailed characteristics of the search query must be determined. In literature databases, the entire metadata of an article can be searched using a search string. By brainstorming or reviewing the common literature, keywords can be identified which delimit the research field. Furthermore, it is important to identify possible synonyms. In addition to the keywords, the publication date, indices, type of publication, etc. can also be used to restrict the search space.

In the sub step “screen for inclusion” the identified articles must be reviewed if they are relevant or not. It is necessary creating inclusion and exclusion criteria to evaluate the articles.

In the sub step “assess quality” [9] checks the quality of the identified articles based on the complete textual information.

In the sub step “extract data” depending on the type of review, different information of an article can be relevant. The required data leads to different extraction procedures. Thus, in a meta-analysis that is connected with a meta-regression, only the required data is collected [9]. In a review, with the aim of opening up the content of a research area, the major focus is on the acquisition of full text information and the subsequent extraction of topics.

The third major step “analyzing literature and reporting the review” comprises the sub steps “analyze and synthesize data” and “report findings”. In the sub step “analyzing and synthesizing data” different analysis steps have to be carried out depending on the type of chosen review. At this point, both qualitative and quantitative analysis methods can be considered. One considerable qualitative analysis method is the qualitative content analysis, in which text components can be categorized based on a codebook [12]. A Co-citation analysis or a semantic similarity analysis can be regarded as quantitative analysis methods. A co-citation analysis links cited articles to identify core articles in scientific literature and offers an opportunity to enhance the comprehension of the intellectual structure [13–15]. Two articles, which have been cited, together by another article are counted as a co-citation [16–18]. Articles with a high number of co-citations therefore have a higher similarity. Relationships between articles can be established not only with the help of citations, but also by analyzing the semantic content. To

establish connections between articles, the content of the identified articles can be subjected to a semantic similarity measurement. Articles with a high number of similar text elements have a higher similarity.

The sub step “report findings” serves to present and interpret the analysis’ results. Furthermore, the sub step should point out opportunities and directions of future research. All novel findings and unsuspected results should be highlighted.

## Adaption And Concretization Of The Systematic Literature Review Process

Following the approach of [9], an adaptation and concretization of the SLR is done in this section to identify current directions of cross-industry innovation (CII) research (see Table. 1). Adaptation means (i) selection or deselection of sub steps from the SLR process by [9] and (ii) extension by newer and particularly fitting elements such as semantic similarity analysis. Concretization is the concrete application of the sub steps. The sub steps “formulate the problem” and “develop and validate the review protocol” are not adapted or concretized as they are necessary for the planning of the study but do not provide any results. In the following the sub steps “search the literature”, “assess quality”, “screen for inclusion”, “extract data”, “analyze and synthesize data” and “report findings” are adapted and concretized.

insert Table. 1 around here

(i) Search the literature - For this study, a database search is applied. The search for the term “cross-industry innovation” in Google Scholar in the period between 2000 and 2018 leads to 872 results. After an examination of the first 200 results to get an impression about the search quality, 64 results are related to cross-industry innovation research. The relevant results are divided into different categories like scientific article, proceedings, scientific books, dissertations, newspaper articles, working paper and articles of predatory journals. The search in Google Scholar offers several issues. First, the search is performed in the entire full text including references. If an article refers to another article with the expression “cross-industry innovation” in the title, the citing article will be identified as CII article based on its citation. Second, a reproducible search in Google Scholar is not possible because the search algorithm is not available. Third, predatory journals are listed in Google Scholar, which leads to lack of quality. Therefore, Google Scholar is not considered as search database.

To increase the recall and the reliability, the literature databases Web of Science (WoS) and Scopus are selected. These databases are among the largest and most comprehensive literature databases in the world [19]. Both databases allow a search by restricting different fields of the metadata. Within the search string, these fields can be linked by Boolean operators (AND, OR, NOT). Five different fields are restricted for the search in Scopus and WoS. The first field is restricted by the keywords. Based on brainstorming, keywords for CII research are searched and synonyms are derived. The major objective in brainstorming

is to abstract the first two word components of the term cross-industry innovation in order to find synonyms. Thus, the synonym "inter" was identified for the term "cross". For the term "industry" the synonyms "sector/sectoral" and "organizational" are identified. No synonyms are searched for the term innovation, as this is the core component of research interests. After the brainstorming, all possible combinations of the brainstorming results are created and saved for further processing. During a first test, by including the word combination "inter-organizational innovation", the amount of data increases exponentially, which leads to a high decrease of precision. Therefore, this term combination is removed from the search string. As a second database restriction, the type of publications is restricted to peer reviewed articles, since these articles are reviewed and should have a higher quality [11]. Consequently, conference proceedings, dissertations or working papers are not considered. As a third database restriction, only articles in English are taken into account, since a semantic similarity analysis is applied a unified language is necessary for further analyses. For the fourth database restriction, the period is limited. The period between 2000 and 2018 will be considered, assuming that research efforts in the field of open innovation have also begun with the emergence of research efforts in the field of CII. For the fifth database restriction, the indices in which journals are listed are restricted to Social Science Citation Index (SSCI), SSCI Expanded, and Emerging Sources Citation Index (ESCI). This ensures that no articles from distant scientific disciplines such as medicine are included. These database restrictions are translated into the query language of WoS and Scopus. The search strings are shown in appendix.

This search leads to the identification of 376 articles in WoS and 343 in Scopus. After a merging and cleaning the data sets from duplicates, 512 articles remain as potential CII articles.

(ii) Assess quality - For this study, in addition to [9] the quality assessment is related to the search string to test whether the search string has a sufficient recall. For this purpose, a basic article of the research field has to be identified. Afterwards, the references and citing articles of the basic article have to be examined to create a comparative data set. Then the search string results and the comparative data set is compared whether the data sets match or whether there are any deviations. If there are deviations, it has to be examined why articles could not be found and an adjustment of the search string is accomplished. Subsequently, sub step "search the literature" is carried out again.

The article [5] is used as basic article and a forward and backward search is applied, which leads to the identification of 29 CII articles. After comparing results of the sub steps "assess quality" and "search the literature", 22 of 29 CII articles can be found in the first data set. The subsequent analysis of the unidentified articles shows that some articles do not use the term "cross-industry innovation" but deal with topics around co-operation or innovation across industry boundaries. For this reason, the search string is extended by the word combinations "analogical thinking innovation", "cross industry alliances innovation", "external problem solver + innovation", "crossing, domain specific boundaries + innovation". Accordingly, with the extended database search string it is possible to identify 27 out of 29 articles. The identification of the remaining two articles would be possible using an additional search string adjustment but this would also lead to an increased number of non-relevant articles, a loss of precision and an enormous assessment effort.

To examine the robustness of the search string, an analysis of the CII related terms “open innovation”, “absorptive capacity” and “knowledge transfer + innovation” is conducted. These terms are taken from the standard literature and can be regarded as theoretical background or directions of CII research. The search is performed in Scopus using the same search string like in sub step “search the literature”. However, the key-words are replaced with the new search terms. Each search term is separately searched. The search term “open innovation” leads to 2566 results. The search term “absorptive capacity” leads to 976 results and the search term “knowledge transfer + innovation” leads to 351 results. In order to investigate how many CII articles can be found in the data set with the respective search term, a sample (confidence interval = 95%; margin of error = 10%) is drawn. This leads to a sample size of 93 articles for the search term “open innovation”, 88 articles for the search term “absorptive capacity”, and 77 articles for the search term “knowledge transfer + innovation”. The maximum percentage share of CII articles in the samples is 2%. All identified CII articles in the samples were also identified by the first search string executed in sub step “search the literature”. Consequently, the implementation of the three presented terms does not lead to an improvement of the recall, rather to a reduction of the precision.

(iii) Screen for inclusion - The research design of this SLR leads to the following inclusion criterion: The study should analyze cooperation or innovation across industry boundaries. Furthermore, the study should focus on a company level not an economic industry perspective.

After an initial review of the title, abstract, keywords the exclusion criteria are established. Following the inclusion criteria, the research focus should lie on cooperation or innovation across industry boundaries. In some cases the term cross industry appears in combination with words like sample, comparison or data which suggests a cross-industry data basis rather than an analysis of CII research. If articles are identified only based on these terms, they will be removed from the data set. The screening for inclusion leads to 48 identified articles.

(iv) Extract data - Data extraction involves downloading and merging metadata from Scopus and WoS on the one hand, and full text articles on the other. Downloading the full text articles is divided into four stage. In the first stage, the 48 full text articles are downloaded from the official pages of the publishers. This can lead to the problem that the university's own library has not concluded a license agreement with the publisher and therefore has no access to the publisher's full text articles. 37 of 48 full text articles can be downloaded. Furthermore, it turns out that in two cases the article's language is stored incorrectly in the databases. Only English articles are searched for, but in two cases, the abstract is in English while the full text is in German. These two articles are removed from the data set. The second stage involves a search on Researchgate. Researchgate is a social media platform that enables scientists to present and share published articles and projects. The remaining nine full text articles are searched on Researchgate and, if available, the authors are contacted and the full text article is inquired. Therefore, three additional full text articles can be procured. In the third stage, the focus shifts to direct contact and the e-mail addresses of the first authors are identified. Afterwards, six authors are directly contacted and five of them reply to share their articles. In the fourth stage, the last article is searched for with the help of interlibrary loan and a copy is obtained. Interlibrary loan is a service where copies of articles can be

searched and requested at other universities. Within this four-stage process, it is possible to obtain all 46 full text articles.

All text information are copied from the available 46 articles and inserted into Excel. Each chapter of an article is assigned to one of seven categories. The categories represent an exemplary structure of a scientific article and include abstract, introduction, da-ta, method, results, discussion, and conclusion. With this categorization, it is possible to analyze selected categories separately or in bundles. Unfortunately, almost every article has a different structure, so that the assignment is partly connected with a bias. In addition to the full text extraction, the articles' metadata from Scopus and WoS are downloaded and consolidated.

(v) Analyze and synthesize data - The data is analyzed on two levels. First, the metadata of the articles are used to display descriptive statistics. Second, the major thematic directions are identified by a semantic similarity analysis and cluster analysis based on the articles full text information. Another possibility would be a clustering based on co-citations but a first test showed that only 27 articles have co-citations of which only 20 articles have more than ten co-citations. The cluster-internally topics of the resulting clusters are slightly consistent. Furthermore, there is a strong time bias in the co-citation analysis. It should be noted that many articles were published in the last three years of the regarded period. Therefore, the number of citations is on a low level. Consequently, the similarity between articles is calculated based on the full text information.

Before the semantic similarities can be measured, however, the data set must first be cleansed [20]. Different filters are used for this purpose using the PatVisor™, an analysis tool of the Institute for Project Management and Innovation [21]. (i) Stop words such as "the" or "and", etc. are removed from the texts. (ii) Roman and Arabic numbers are removed, as they have no relevance to the content. (iii) Synonyms are harmonized using a search and replacement filter to make the nouns used consistent in the data set. (iv) Furthermore, conjugated verbs must be converted to their infinitive form using a lemmatizer. Nouns that occur in the plural are transformed into their respective singular forms [20]. The similarity of texts to each other is determined with the help of a semantic analysis. Thereby word combinations are formed, extracted, counted and compared with each other to measure similarities [22]. The calculation between the articles is done based on bi-grams with a minimum word length of three in a word window of four. Thus, word combinations of two words are compared with each other. All text information except images, formulas and references from the articles are taken into account for the similarity calculation. In order to obtain meaningful similarity values, filters are applied which filter out stop words, numbers and unify synonyms. Since numbers pro-vide no added value in terms of content, they are identified and deleted using a Roman and Arabic number filter. In addition, a lemmatizer is applied which transforms conjugated verbs into their infinitive forms and Nouns in plural to their respective singular forms. Finally, the articles are searched for abbreviations and synonyms and these are unified with the help of a synonym filter. Following [23] or [24], the linkage type complete linkage type b and c, and the similarity coefficient double single-sided-inclusion is selected. Since the size of the available full text articles varies

greatly and the double single-sided-inclusion coefficient takes into account the different text length between comparative articles, this coefficient is the right choice.

The cluster analysis is applied in a two-step procedure. In the first step outliers have to be identified. Therefore, a cluster analysis using the single linkage method is applied for all 46 articles. The method combines the most similar articles systematically to form clusters. Especially dissimilar articles are clustered at the end of the procedure. Articles that are clustered at the end of the method's procedure are outliers and eliminated. The cluster procedure is implemented in the programming language R with the function hclust. The dissimilarity matrix is read and the function hclust is executed. In addition, to identify outliers the corresponding dendrogram is analyzed. A dendrogram is a graphical illustration of a hierarchical cluster formation in the form of a tree structure. By means of a dendrogram, the point of clusters' union or division can graphically identified [25]. The similarity in the data set is on a low level. This can be related to the thematic distance as well as to the style of writing. Based on the dendrogram, the last six added articles are removed, since the overall distance level is very high. These six articles are additionally reviewed which leads to the insight that the research of these articles seems to be far away from the core CII research field.

(vi) Report findings—The findings are divided into two parts. The evaluation of the different cross-industry innovation directions and a discussion about future research based on the creativity technique morphological box. The morphological box is a creativity technique based on [26], which is a method to identify solutions in multi-dimensional and complex environment. The morphological box is built on parameters and their corresponding specifications. A complex problem can be divided into its independent parameters and possible specifications. A followed holistic view on the combination of the different parameters' specifications leads to diversified solution space. This method can be used to find opportunities or needs for future research.

## Reporting The Results Of The Review

This section presents the results of the descriptive statistics plus the semantic similarity and cluster analysis. First, the descriptive statistics are presented, followed by the semantic similarity and cluster analysis. Finally, the resulting clusters are examined in detail.

### 1.1 Descriptive statistics

Scopus and Web of Science (WoS) offer a large number of evaluable fields, which can be different. The field "research field", for example, which gives a rough classification of a research field, is only available in the Scopus. In order to give an overview of CII research, the following section describes the development of articles over time, the journals in which the most active researchers have published, which countries are involved in the research field, and an analysis about the most cited articles.

First, the search string is limited to the period 2000-2018 (see Fig. 2). The first publication occurs in 2003. Between 2004 and 2009, additional four articles are published, but only a maximum of one per year. It seems that fundamental research is undertaken to define the research field. With regard to the developing research in the field of open innovation, which was shaped by [2], it is reasonable that the number of publications is on a low level, since CII research can be seen as a sub-research area of open innovation. Therefore the articles from 2003-2006 can be seen as basic research in the field of CII. Between 2010 and 2018, the number of articles per year is alternating. A higher activity can be seen, reaching a maximum of nine publications in 2016. It seems that the interest in this research field is growing.

*insert Fig. 2 around here*

Second, in addition to the time series, the journals in which the articles are published are also of interest. Each journal has its own aim and scope and such information could provide insights about the research aim of an article whether the article focuses on theoretical or a practical approach. Fig. 3 shows the leading journals in which at least more than one CII article is published. The articles are spread over 28 journals. Except the Food Journal, all journals are originated in the field of technology, innovation and entrepreneurship (TIE). The R&D Management Journal leads this ranking, with five articles, followed by International Journal of Innovation Management (4), Research Policy (3) and Technovation (3). Within the research field of TIE, the articles are distributed to a wide range of journals.

*insert Fig. 3 around here*

Third, the evaluation of the authors gives information to leading scientists in the field of CII (see Table 2). The 46 identified articles are written by 92 different authors. Ellen Enkel leads the ranking with nine articles. She is involved in 20% of all identified CII articles. Thus, it can be stated that she is one of the most influential researchers in the field of CII. Ellen Enkel is followed by Oliver Gassmann and Sebastian Heil, each with four articles. Some of these articles are also published in co-authorship with Ellen Enkel.

*insert Table 2 around here*

Fourth, closely associated with the authors is the country distribution. For this purpose, the country codes of the corresponding affiliations from the metadata are used. Since several authors can submit an article, a weighting is calculated and presented based on the overall sum of countries' percentage share at the articles (see Table 3). Most of the research originates from Germany. German institutions have a percentage share of 42 % on CII research articles. The United States of America follows with a big leap with a percentage share of nearly 8.7 %. The United Kingdom and France have both a percentage share of 6.5 %. 18 nations are involved in the CII research, with the first four nations responsible for 63.7% of the research.

*insert Table 3 around here*

Fifth, the citations are used to identify influential publications. When looking at the citations per publication, four articles are characterized by a high number of citations. [5] is the most cited article with

140 citations. This is followed by [27] (70 citations), [28] (58 citations) and [29] (40 citations). These four publications can be classified as very influential. They are followed by 15 articles with a citation rate between 15 and 39. 11 articles can be classified having a weak influence because these articles have less than 10 citations. 30 articles have not any citations, which is not necessarily surprising, since it takes a certain amount of time for an article to be cited.

## 1.2 Semantic similarity measurements and cluster analysis –

The clustering of the remaining 40 articles is done by hierarchical cluster analysis based on the Ward method. This cluster method is also realized with the function `hclust` in the programming language R using the dissimilarity matrix. Since six articles have been removed from the data set, the similarity measurement is performed again for the 40 remaining articles with the same settings. Using the resulting dendrogram and the scree plot, the number of clusters is determined. To determine the number of clusters, first the scree plot is used and the elbow criterion is applied [30]. According to this criterion, the number of clusters should be five. In this case, the elbow criterion serves only as a rough orientation, since the scree plot is irregular. Therefore, the number of clusters is varied to check if there is a better solution. In addition to the five-cluster solution, the six-cluster solution is tested. The six-cluster solution divides a relatively large, undefined cluster into two smaller but more consistent clusters. Therefore, the six-cluster solution is selected for further analyses.

By means of multidimensional scaling (MDS), the similarities and the identified clusters can be illustrated on a map. The MDS is a technique, which allows visualizing dissimilarities on a map having the objective to represent the distances as good as possible [31]. For this study, a MDS is created based on the similarity matrix and the Euclidean distance measurement. Furthermore, the articles of six clusters are highlighted at the MDS with different symbols (see Fig. 4). In general, the stress value according to [32] is used as the value for the quality of the MDS. For this MDS the stress value is 0.21, which is a value that titles a relatively weak significance of the MDS. Evaluating the MDS all articles from cluster 4 are relatively close to each other. Furthermore, clusters 3 and 6 show a relatively large dispersion on the map.

*insert Fig. 4 around here*

By means of the cluster analysis six clusters were identified which are described in the following (see Table 4).

*insert Table 4 around here*

Cluster one (C1) contains two articles both dealing with the measurement of technological distance on company level. In both articles, patent data are used and different measuring methods are listed and compared. Furthermore, the small sample size is mentioned as a limitation. In addition, the indicators are based on patent data; on the one hand, not all technologies are patentable and, on the other hand, there

are other intellectual property rights like trademarks or utility models, which were not considered for the measurement.

The second cluster (C2) contains two case studies of CII in Italy's food and pharmaceutical industry. The cluster includes two articles from 2016, which use the CII theory for "exploring to what extent external knowledge sourcing affects innovation" and "how internal and external drivers affect innovation in Italian food industry" [35, 36]. The studies identify an increased need for absorptive capacity and cooperation with universities for knowledge transfer and product innovation. Again, the sample size is listed as a limitation. Therefore, the results are representative in a limited way.

The third cluster (C3) has a very broad thematically base. It comprises 17 articles in the period between 2009 and 2018. The research questions of this cluster are not positioned at the core research field namely absorptive capacity, knowledge transfer and CII processes. The third cluster including CII case studies [27, 42, 44]. However, [51] attempt to develop identification methods for a specific type of CII. Furthermore, the topics knowledge sharing [47], inter-sectoral technological integration [49], knowledge transfer [38] are mentioned.

The fourth cluster (C4) primarily comprises research on absorptive capacity. It comprises seven articles published in the period between 2010 and 2018. Both qualitative and quantitative research methods are used in this cluster. Partial least square modelling and trivariate probit model are used as quantitative methods. Interviews and multiple case study analyses are used as qualitative methods. Objectives of the articles are the investigation of absorptive capacity's determinants [69]. [54] investigates how to build potential absorptive capacity for distant collaboration in order to obtain radical solutions. Furthermore, [53] examines a case study (for the company Henkel) how firms systematically learn from distant partners across industry boundaries. [28] examines the influence of absorptive capacity on different types of knowledge. Knowledge from companies' own industry, knowledge from other industries and knowledge from research institutions are examined. [28] mentions that R&D intensity does not significantly influence the absorptive capacity for inter- and intra-industry knowledge. [58] relies on absorptive capacity research to investigate how social integration mechanisms in distant collaborations can be translated into different learning outcomes. It turned out that social integration mechanisms complement the absorptive capacity in exploration, exploitation phases for external knowledge. [57] focuses on the firm's exploration and exploitation strategy and the associated driving factors of absorptive capacity. [56] focuses on absorptive capacity research and investigates how socialization facilitates knowledge transfer. To sum up the limitations for this cluster, there is generally a limited sample size, which leads to a limited representativeness.

The fifth cluster (C5) primarily comprises research in the field of knowledge transfer, i.e. how knowledge can be searched, abstracted, identified and adapted. It comprises six articles published in the period between 2010 and 2018. Most of the research methods used in this cluster have a qualitative nature. In addition to qualitative research, conceptual research is applied in one article and a mixed method approach is chosen in another one. [62] uses structural equation modeling in combination with a

bivariate correlation analysis for the mixed method research. Interviews and multiple case study analysis are used for qualitative research. [63] investigates the influence of proximities to establish a conceptual model of knowledge transfer. [62] examines the motivational influences of experts in relation to participation in CII workshops. [61] examines how a firm applies searches within its innovation activities. It turns out that abstraction plays an important role. Furthermore, it is possible to successfully develop products without having a high level of knowledge source breadth and search activity depth. [60] investigates the role of intermediaries in the CII process. Three types of intermediaries can be identified which have different approaches in the realization of innovations. As a limitation, it should be noted that only successful CII projects have been investigated. Failed projects should be used for future research. [59] develops a systematic search process for CII. This article distinguishes from the other articles of the cluster. Instead of absorptive capacity, [59] focuses on research around cognitive distance and whether it has a positive or negative influence on CII.

The sixth cluster (C6) comprises research about process models and analogies. Cluster six contains six articles published in the period between 2005 and 2016. This cluster includes the first publication in the data set and is to be understood as the core research on CII through two conceptual articles. Within the two conceptual articles, process models for the generation of innovations are presented [29, 64]. In addition to conceptual approaches, qualitative and quantitative research methods are also applied in this cluster.

## Perspectives In A Morphological View

From the previously described clusters, in combination with the morphological box, eight different parameters of CII research are identified (see Table 5). The parameters may have different specification. (1) The first parameter is called "research design", which is distinguished between the specifications qualitative, quantitative or mixed method. (2) The second parameter is the "data basis", which is distinguished between the specifications survey, patent, interview and customer innovation survey. (3) In the development or exploitation of knowledge, different CII types occur, which leads to the third parameter "CII types" and differs in the specifications outside-in, inside-out and coupled. (4) Some authors mention the radicalness of CII, which leads to the fourth parameter "degree of innovation" with the specifications radical or incremental. (5) Many authors do not exactly specify the cooperation structure or focus on the analysis of two partners, which leads to the parameter "number of CII partners" with the specifications 2, 3 or greater than 3. (6) The sixth parameter is the "cultural composition" of CII partners, i.e. whether the partnership is national or international. The parameter "cultural composition" is derived with the specifications national and international. (7) In some articles, the small sample size with the associated limited representativity is notice-able. Thus the seventh parameter "sample size" is derived with the specifications 1–50, 51–100, >100. (8) Using cluster analysis, six research directions were identified, which leads to the seventh parameter "research direction" with the specifications distance measurement, food pharma case study, diversified spectrum, absorptive capacity, knowledge transfer, and processes and analogies.

insert Table 5 around here

Based on a morphological box different needs for future research can be identified in case of cross-industry innovation research. (i) The literature concerning CII processes focuses on the outside-in process of CII for knowledge transfer. A variation for future research should be the focus on the inside-out or the coupled process. (ii) [35] and [36] examine aspects of cross-industry innovation in the food and pharmaceutical industry. Their findings could be verified by the analyzation of case studies in other industries like smart home, bionic, autonomous driving, and industry 4.0. (iii) The number of CII partners currently plays a minor role. Whereby an increase in the number of partners leads to a more complex form of knowledge transfer or absorptive capacity. So that a need for the investigation of more complex CII is necessary based on the number of the partners.

## List Of Abbreviations

C1 = Cluster 1

C2 = Cluster 2

C3 = Cluster 3

C4 = Cluster 4

C5 = Cluster 5

C6 = Cluster 6

CII = Cross-Industry Innovation

ESCI = Emerging Sources Citation Index

MDS = Multidimensional scaling

SLR = Systematic literature review

SSCI = Social Science Citation Index

TIE = Technology, Innovation and Entrepreneurship

WoS = Web of Science

## Declarations

### Ethics approval and consent to participate

Not applicable

# **Consent for publication**

Not applicable

## **Availability of data and material**

The datasets during and/or analysed during the current study available from the corresponding author on reasonable request.

## **Competing interests**

The authors declare that they have no competing interests

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## **Authors' contributions**

Every work in this paper is done by TM. TM read and approved the final manuscript.

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## Tables

Table 1. Adapted and concretized systematic research process

Sub steps	Adaptation	Outcomes
Formulate the review and validate the review protocol	no adaptation	research question
	no adaptation	review protocol
Search the literature assess quality screen for inclusion extract data	combined database search	rough data set
	search string assessment and recall check	improved search string
	no adaptation	cleansed data set
	full text information extraction	cleansed and extracted data set
Analyze and synthesize data Report findings	semantic similarity measurement	Applied analyzation methods
	morphological view on future research	summarized research directions

Table 2. Top 10 authors in cross-industry innovation research

Author	Number of publications
Enkel, E	9
Heil, S	4
Gassmann, O	4
Broering, S	3
Bader, K	2
Sick, N	2
Poetz, M K	2
Carraresi, L	2
Ciliberti, S	2
Zeschky, M	2

Table 3. Geographical distribution of cross-industry innovation articles

Country	Percentage share
Germany	42
United States	8.7
United Kingdom	6.5
France	6.5
Italy	5.2
Switzerland	5
Norway	4.4
Japan	4.4
Denmark	3.9
Sweden	3.7
Russia	2.2
Taiwan	2.2
Austria	1.5
Belgium	1.1
Singapore	0.7
China	0.7
Netherlands	0.7
Spain	0.7

Table 4. List of cross-industry innovation articles

Author	Title	Year	Cluster
[33] vom Stein et al.	How to measure technological distance in collaborations - The case of electric mobility	2015	1
[34] Simon and Sick	Technological distance measures: new perspectives on nearby and far away	2016	1
[35] Caiazza et al.	Drivers of innovation in Italy: Food versus pharmaceutical industry	2016	2
[36] Ciliberti et al.	External knowledge sources as drivers for cross-industry innovation in the italian food sector: Does company size matter	2016	2
[37] Li and Vanhaverbeke	The effects of inter-industry and country difference in supplier relationships on pioneering innovations	2009	3
[27] Gassmann et al.	Crossing the industry-line: Breakthrough innovation through cross-industry alliances with 'Non-Suppliers'	2010	3
[38] Plum and Hassink	On the nature and Geography of innovation and interactive learning: A case study of the biotechnology industry in the Aachen technology region, Germany	2011	3
[39] Buganza et al.	Organisational implications of open innovation: An analysis of inter-industry patterns	2011	3
[40] Gandia	The digital revolution and convergence in the videogame and animation industries: Effects on the strategic organization of the innovation process	2013	3
[41] Lew and Sinkovics	Crossing Borders and Industry Sectors: Behavioral Governance in Strategic Alliances and Product Innovation for Competitive Advantage	2013	3
[42] Larsson and Lindstroem	Bridging the Knowledge-gap Between the Old and the New: Regional Marine Experience Production in Orust, Västra Goetaland, Sweden	2014	3
[43] Levén et al.	Managing research and innovation networks: Evidence from a government sponsored cross-industry program	2014	3
[44] Tsujimoto et al.	Finding the 'boundary mediators': Network analysis of the joint R&D project between Toyota and Panasonic	2014	3
[45] Tatyarynowicz et al.	Environmental Demands and the Emergence of Social Structure: Technological Dynamism and Interorganizational Network Forms*	2016	3
[46] Bornkessel et al.	Cross-industry Collaborations in the Convergence Area of Functional Foods	2016	3
[47] Amitrano et al.	Knowledge sharing in innovation ecosystems: A focus on functional food industry	2017	3
[48] Hauge et al.	Developing cross-industry innovation capability: regional drivers and indicators within firms	2017	3
[49] Corradini and De Propris	Beyond local search: Bridging platforms and inter-sectoral technological integration	2017	3
[50] Zhang and Cantwell	Exploration and exploitation: The different impacts of two types of Japanese business group network on firm innovation and global learning	2017	3
[51] Mahnken and Moehrle	Multi-cross-industry innovation patents in the USA - A combination of PATSTAT and Orbis search	2018	3
[52] Filiou and	Industry cognitive distance in alliances and firm innovation	2018	3

Massini	performance		
[28] Schmidt	Absorptive capacity-one size fits all? A firm-level analysis of absorptive capacity for different kinds of knowledge	2010	4
[53] Bader	How to benefit from cross-industry innovation a best practice case	2013	4
[54] Enkel and Heil	Preparing for distant collaboration: Antecedents to potential absorptive capacity in cross-industry innovation	2014	4
[55] Heil and Enkel	Exercising Opportunities for Cross-Industry Innovation: How to Support Absorptive Capacity in Distant Knowledge Processing	2015	4
[56] Dingler and Enkel	Socialization and innovation: Insights from collaboration across industry boundaries	2016	4
[57] Enkel et al.	Exploratory and exploitative innovation: To what extent do the dimensions of individual level absorptive capacity contribute?	2017	4
[58] Enkel et al.	Managing technological distance in internal and external collaborations: absorptive capacity routines and social integration for innovation	2018	4
[59] Brunswicker and Hutschek	Crossing horizons: Leveraging cross-industry innovation search in the front-end of the innovation process	2010	5
[5] Enkel and Gassmann	Creative imitation: Exploring the case of cross-industry innovation	2010	5
[60] Gassmann et al.	The role of intermediaries in cross-industry innovation processes	2011	5
[61] Horváth and Enkel	When general recommendations fail: How to search in single innovation project settings	2014	5
[62] Enkel and Bader	Why do experts contribute in cross-industry innovation? A structural model of motivational factors, intention and behavior	2016	5
[63] Lyng and Brun	Knowledge Transition: A Conceptual Model of Knowledge Transfer for Cross-Industry Innovation	2018	5
[64] Herstatt and Kalogerakis	How to use analogies for breakthrough innovations	2005	6
[29] Gassmann and Zeschky	Opening up the solution space: The role of analogical thinking for breakthrough product innovation	2008	6
[65] Sheu and Lee	A proposed process for systematic innovation	2010	6
[66] Poetz and Pruegl	Crossing domain-specific boundaries in search of innovation exploring the potential of pyramiding	2010	6
[67] Franke et al.	Integrating problem solvers from analogous markets in new product ideation	2014	6
[68] Kim and Horii	Analogical thinking for generation of innovative ideas: An exploratory study of influential factors	2016	6

Table 5. Morphological box of cross industry innovation research

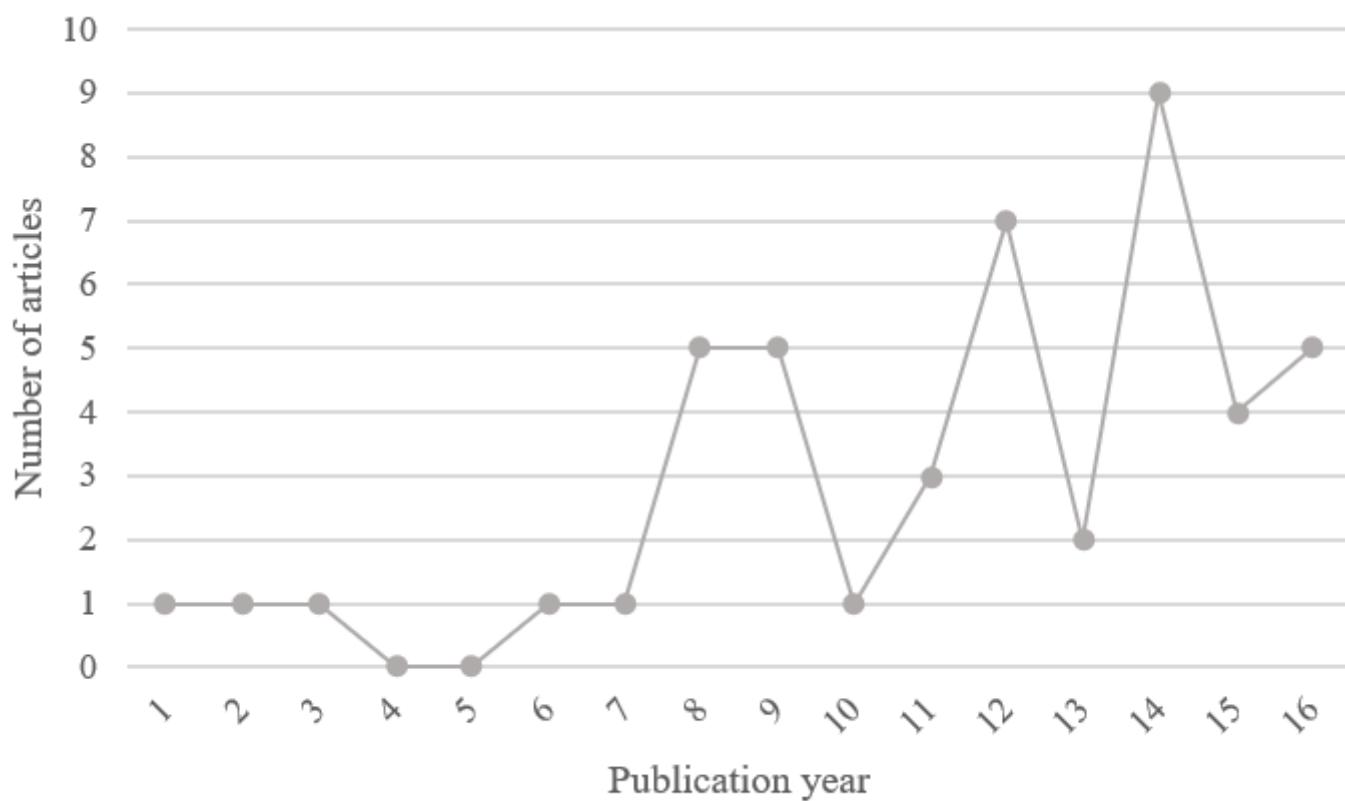
Parameters	Specifications				
Research design	qualitative		quantitative		mixed method
Data basis	survey	patent	interview	customer innovation survey	
CII types	outside-in		inside-out		coupled
Degree of innovation	radical		incremental		
Number of CII partner	2		3		>=3
Cultural composition	national			international	
Sample size	1-50		51-100		>100
Research direction	distance measurement	case study	diversified spectrum	absorptive capacity	knowledge transfer processes and analogies

## Figures



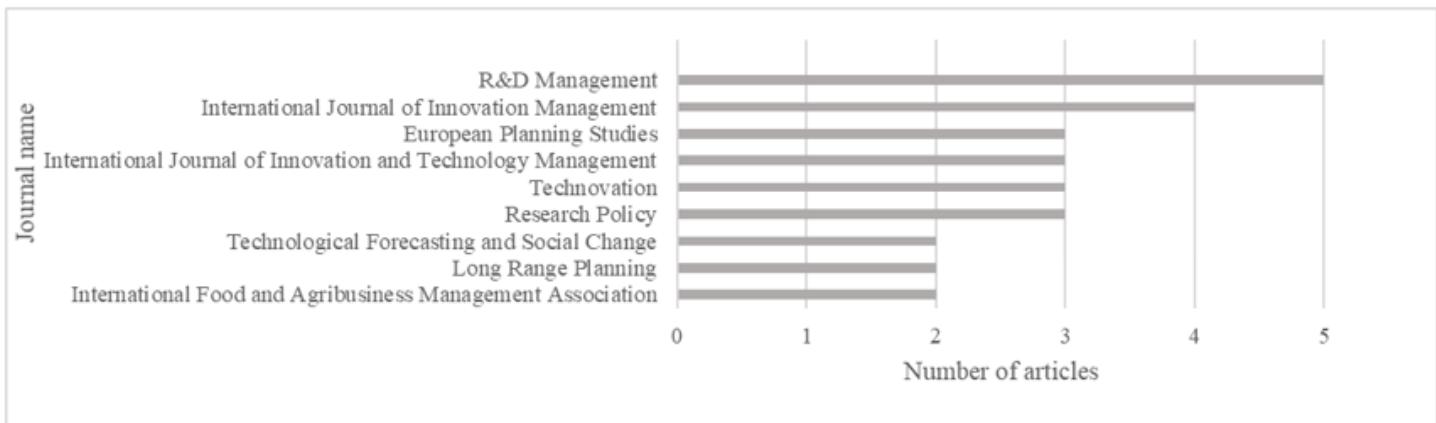
Figure 1

Systematic literature review process [9]



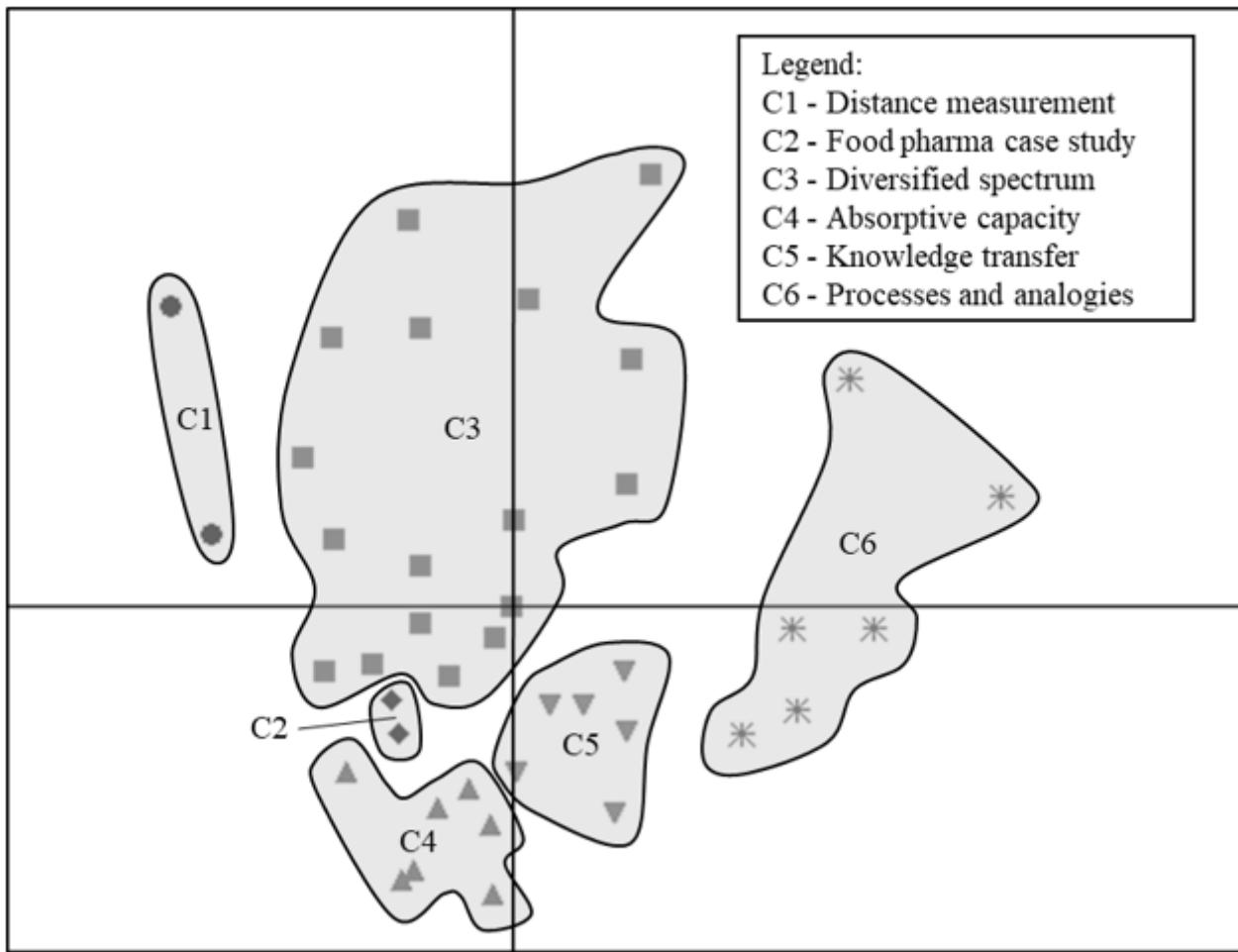
**Figure 2**

Time series of 46 identified cross-industry innovation articles, sorted by publication year



**Figure 3**

Journals in cross-industry innovation research with more than one published article



**Figure 4**

Multidimensional scaling of cross-industry innovation articles

## Supplementary Files

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