Looking ahead!

Predicting the upcoming start of large-scale diffusion of radically new high-tech innovations

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Predicting the upcoming start of large-scale diffusion of radically new high-tech innovations

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Shashank, you will always be remembered.

Executive Summary

PURPOSE

Knowing the time point of large-scale diffusion (see Figure 1) of a radically new high-tech innovation is a highly relevant topic. Companies can plan their research and development efforts, production, as well as marketing plans according to the predicted time point of large-scale diffusion. Moreover, government institutions and researchers can also benefit from a forecast because of increased insights and transparency into the diffusion process.

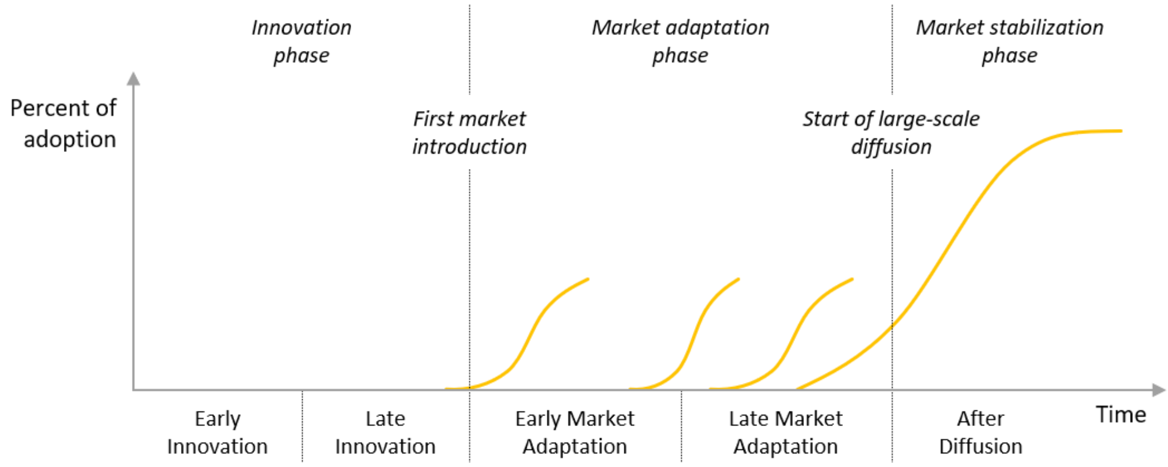

Figure 1: Diffusion curve for radically new high-tech innovations

The research is based upon the assumption that specific indicators can predict the start of large-scale diffusion. Hence, various indicators were needed that observe mechanisms that can predict the emerging start of large-scale diffusion. These indicators should cover holistically the innovation itself, but also the environment around and innovation and the innovating firm.

METHODOLOGY

The scientific field of forecasting the start of large-scale diffusion is relatively new. Therefore, an explorative methodology was required for this research. During the explorative process, it was ensured that indicators reflect on the holistic environment of an innovation by minding the so-called data collection cube. The cube has the following three dimensions: (i) indicator sources, (ii) indicator classes, and (iii) indicator types. Indicators can stem from three sources: scientific literature, expert interviews, and case studies. Only scientific literature has been used for this master thesis due to the limited time available (selected scientific branches are diffusion forecasting, macroenvironment, dominant design, crossing the chasm, disruptive innovations, and pre-diffusion). A check for completeness, based upon findings of the pre-diffusion branch, has shown that the scientific literature covers most of the holistic environment. Nevertheless, the other two sources were recommended for future research to customize the findings to a specific innovation or industry.

Moreover, to ensure that a holistic perspective and different kinds of indicators are used to predict the start of large-scale diffusion, different (ii) indicator classes (market, technology, and contextual) and (iii) types (quantitative, qualitative, and dichotomy) were considered.

A data selection funnel (see Figure 2) was created, narrowing scientific branches down to a list of indicators in three steps. Each of these steps has its own criteria designed to:

- Select scientific branches with the highest potential to find results in the literature reviews
- Derive indicators that can observe the diffusion
- Select indicators that can predict the start of large-scale diffusion

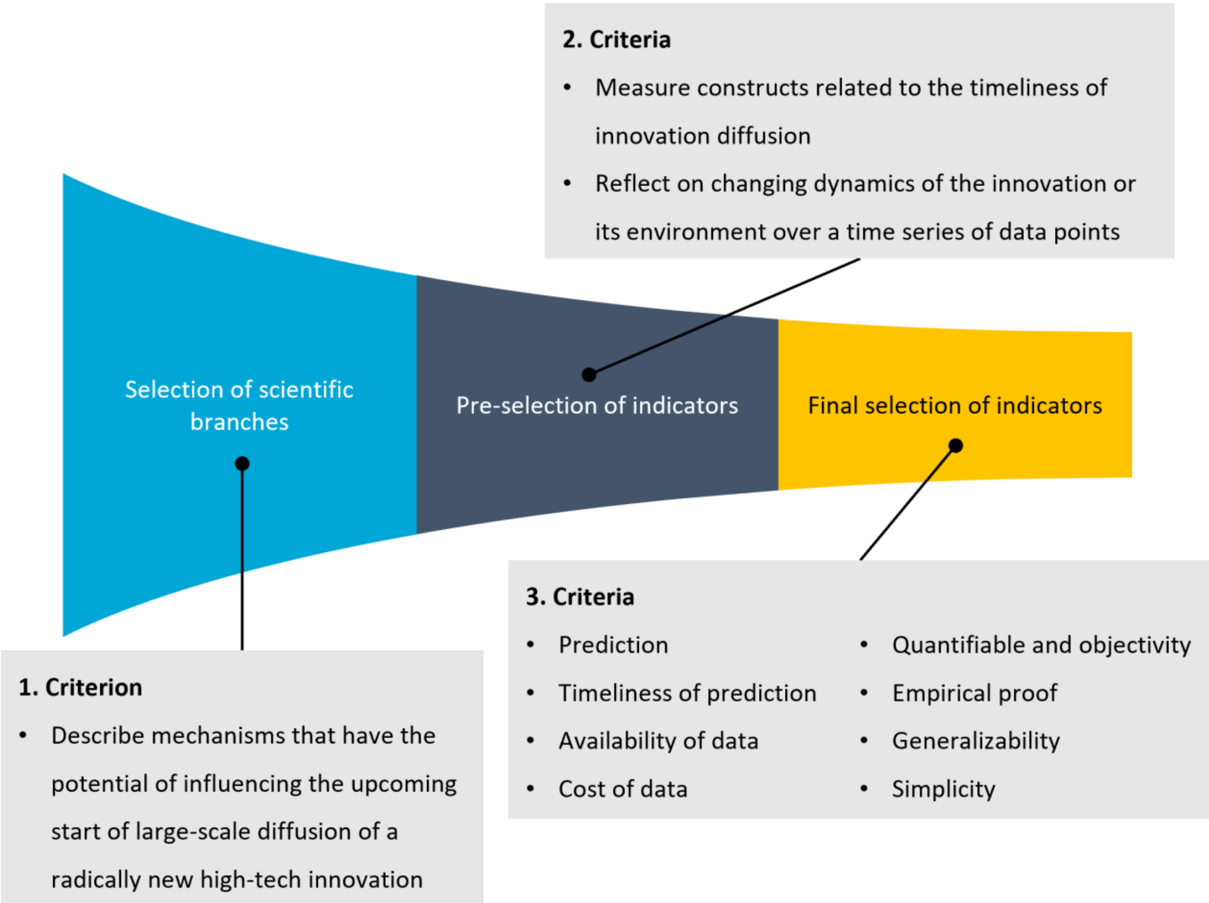

Figure 2: Data selection funnel

The last step of the data selection funnel, selecting the indicators which can actually predict, was carried out with the support of three researchers. Eight criteria were used to select the most potential indicators: (i) *Prediction*, (ii) *Timeliness of prediction*, (iii) *Availability of data*, (iv) *Cost of data*, (v) *Quantifiable & Objectivity*, (vi) *Empirical proof*, (vii) *Generalizability*, (viii) *Simplicity*. The researchers were asked to evaluate the indicators according to the criteria (i) *Prediction* and (vi) *Empirical proof* as part of the scientific quality gate selecting the most potential indicators.

After the indicators have been evaluated, a sensitivity analysis has been performed to improve the robustness of the selection mechanisms and to rule out an arbitrary selection of the indicators. Out of 50 indicators found in the literature or derived from the literature, 38 indicators were selected according to the selection mechanism. These 38 indicators have been split into two sets of judgemental and non-judgemental indicators to prepare the design of the forecasting approach.

FINDINGS

The forecasting approach aims to guide a user towards the correct forecasting technique given an innovation and situation. For the forecasting approach, various forecasting techniques have been explored in a literature review. As a result, five forecasting techniques were found to be fitting the objective to predict the start of large-scale diffusion: (i) assumptions-based modelling, (ii) Delphi method, (iii) analogous forecasting, (iv) time series & regression models, and (v) artificial neural networks. However, each of the five forecasting techniques has disadvantages that can be overcome by one of the other methods. Hence, the forecasting approach has two stages. First, the user is guided towards the primary method and subsequently towards an additional method overcoming the disadvantages of the first method and improving the overall reliability of the forecast (see Figure 3). For each method, a set of indicators is recommended that has been carefully selected to fit the forecasting technique.

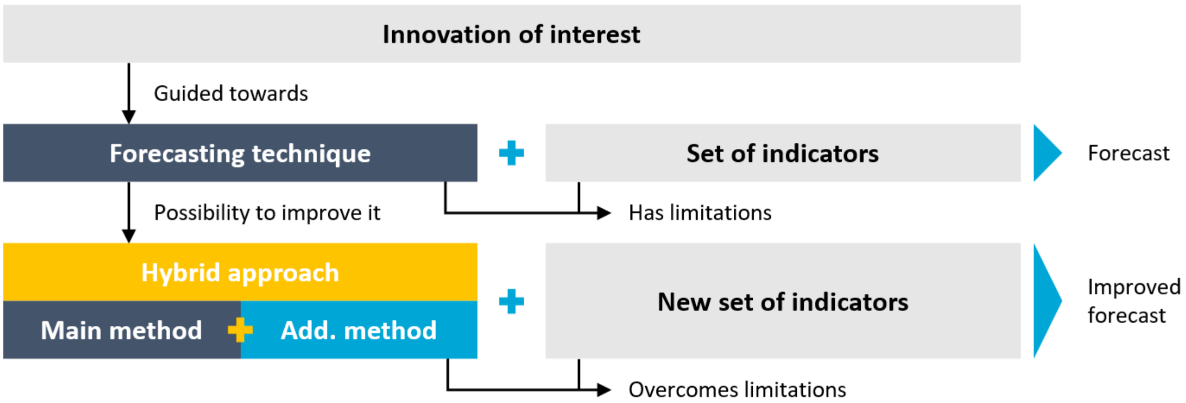

Figure 3: Overview of the forecasting approach

VALIDATION

Once the forecasting approach has been developed, the completeness of indicators has been checked by using Ortt & Kamp's 14 factors influencing the pre-diffusion phase. Additionally, four validation interviews applying the research on green hydrogen have been performed to let external actors reflect on the practical relevance, criteria, indicators, and the forecasting approach in general. These validation interviews formed the practical quality gate forging a bridge to the earlier mentioned scientific quality gate.

SCIENTIFIC CONTRIBUTION

The research contributes in six ways towards the scientific field of forecasting the start of large-scale diffusion. Because the scientific field is relatively new, not much research has been done so far. This thesis aimed to create a basis for future research by:

- Designing a research methodology to derive indicators and select them systematically
- Developing criteria to evaluate predictive indicators
- Giving an overview of relevant forecasting techniques
- Describing characteristics, advantages, and disadvantages of the forecasting techniques

- Guiding researchers and practitioners towards a forecasting technique and its indicators based upon a forecasting approach incorporating hybrid approaches of forecasting techniques
- Deriving and evaluating independent variables for the prediction of the start of large-scale diffusion

Moreover, it was found that the 14 factors by Ortt & Kamp give a holistic overview of the pre-diffusion phase and its mechanisms influencing the diffusion. Although the factors have been developed for another use case, they can also aid to predict the start of large-scale diffusion of a radically new high-tech innovation.

Keywords: diffusion, innovation, pre-diffusion phase, prediction, indicator, forecasting technique, green hydrogen

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Nevertheless, Roland taught me to focus on the right sections and encouraged me to work on the thesis even during challenging times. Furthermore, I express my gratitude towards all interview candidates. Your opinions, experiences, and comments were helpful for me and improved the thesis substantially.

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Florian Thomas Schmidt
Delft, 15th August 2021

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1 Introduction

Companies that enter the market with their product shortly before the growth of a radically new technology starts are usually very successful (Golder & Tellis, 1997; Ortt et al., 2007; Suárez et al., 2015). These companies diffuse their product when the customer needs are better known, the technology is sufficiently developed, and the market is ready. From the retro perspective, it is easy to define the right timing for market entry. But how can a company predict the perfect moment to enter the market with their new product? What indicators anticipate the moment before large-scale diffusion?

This master thesis will explore various scientific branches describing the upcoming large-scale diffusion of radically new high-tech innovations. From there, I will derive indicators that can observe the upcoming start of diffusion, which subsequently will be evaluated regarding their predictive capabilities. Lastly, a forecasting approach will be developed, combining holistic indicators and forecasting techniques, guiding companies and researchers to predict the upcoming large-scale diffusion of radically new high-tech innovations.

The subject of large-scale diffusion in innovation management is not an entirely new topic and has been discussed already by various scholars, as the literature review will show. However, most models laid out their focus on sales forecasting at the peak point. Only a few models discuss the early period of growth. However, mostly they do not define and explain it sufficiently (Suárez et al., 2015). This lack of scientific explanation of the early period brings us to the research objective for this master thesis.

1.1 Research objective

As mentioned before, most models of product diffusion lack a focus on the pre-diffusion phase. However, this phase is crucial for companies to make decisions regarding their research and development, production, and the marketing mix, to just mention a few. At the same time, some factors cannot be directly influenced by a company. For example, sociocultural and macro-economic aspects, technology and application knowledge, and resource availability are factors that heavily influence an innovation's success (Ortt et al., 2014). However, these factors do not lie in the radius of operation of companies. Therefore, companies need to know when an upcoming diffusion of an innovation is likely. Companies can then align their efforts for the perfect time of entry. Therefore, the main research question guiding the master thesis is:

How can researchers and companies predict the upcoming large-scale diffusion of a radically new high-tech innovation?

The main research question is accompanied by the following sub research questions to structure the research further:

SRQ1: Which forecasting techniques can predict the start of large-scale diffusion?
SRQ2: What characteristics does each forecasting technique have?
SRQ3: Which perspectives are relevant to derive observing indicators of large-scale diffusion of radically new high-tech innovations?

SRQ4: Which indicators can be used to observe the large-scale diffusion of radically new high-tech innovations?
SRQ5: Which criteria can evaluate if an observing indicator can predict?
SRQ6: Which of the observing indicators can predict the large-scale diffusion of a radically new high-tech innovation?
SRQ7: How can these indicators be combined into a forecasting approach to predict the large-scale diffusion of radically new high-tech innovations?
SRQ8: What are validation methods to confirm the research regarding its face validity?

1.2 Focus of the master thesis

Innovations can be assessed from different perspectives and levels. Various researchers have defined three levels of innovations depending on their reach and influence (e.g. for sustainable innovations and policies: Geels et al., 2017). In a more general approach, without a specific emphasis on sustainable innovations, Ortt (2020) sees innovations on the following three levels:

- Project level: How are innovations developed and diffused internally by one company as a product or service?
- Pattern level: How do similar innovations by different companies and industries diffuse?
- Discipline level: How do innovations emerge in a scientific field or discipline?

This master thesis will focus on the pattern level. Innovation projects by various companies are summarized and seen as one innovation that diffuses into the market. This level allows us to see how innovations diffuse and make predictions when an innovation diffuses for the first time into the mass market neglecting the company behind it.

This level fits well the research objective discussed previously. A researcher or company would like to know when a specific innovation reaches the mass market. For finding the timepoint, it is irrelevant for now which company will diffuse with the innovation. Which company diffuses first is out of the scope of the master thesis and requires additional research.

1.3 Introduction of key terminology

The following two sections will explain the key terminology radically new high-tech innovations and the start of large-scale diffusion.

1.3.1 Radically new high-tech innovations

The typology to name innovations is diverse and complex. For this master thesis, I will focus on innovations radically new to the market in the sector of high-tech innovations. Garcia & Calantone (2002) shed some light on the definitions of various types of innovation. Following their work, I define radically new high-tech innovations as products or services embodying a new technology or a technology used in a new functionality leading to a discontinuity in the market. However, some of the findings in Sections 3.2.3, 3.2.4, and 3.2.5 also incorporate general consumer durables.

1.3.2 Start of large-scale diffusion

Chandrasekaran & Tellis (2007, p. 39) define diffusion as "the spread of an innovation across markets over time". This definition is straightforward but sufficient because the diffusion is defined apart from other concepts, e.g. strategic niche management describing mainly social drivers (Schot & Geels, 2008), and focuses purely on the mechanistic and measurable concept of sales of a product in the market. Other concepts such as strategic niche management may be used as an explanation of indicators of sales growth. However, such concepts do not define the start of innovation diffusion because, until now, it has not been agreed on a unified reason. This explanation is also the reason why various scientific branches are explored to derive the predictive indicators.

Researchers tend to be divided about the reasons until an innovation diffuses in the mass market. Although scientists use different explanations for the reasons of the time until the sales take-off, and therefore also different indicators, it is possible to use Golder and Tellis's definition because of its neutrality. Golder and Tellis (2004, p. 208) see the sales take-off as a "first dramatic and sustained increase in product category sales" (see Figure 4).

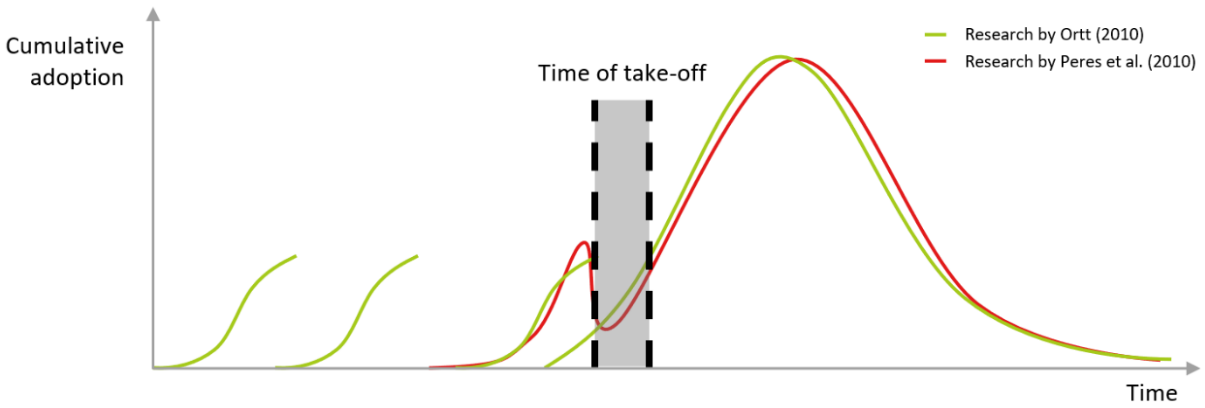


Figure 4: Comparison of diffusion theories (adapted from Ortt, 2010; Peres et al., 2010)

One explanation for the different reasons is the level of explanation used for the theories. Ortt describes a variety of niche applications on a pattern level, while Peres et al. focused on one application of a technology on a project level. Visually the two theories tend to look very similar, excluding the early part of niche diffusion. However, Peres et al. perspective might be deceptive for predicting the start of large-scale diffusion as similar innovations might diffuse in unforeseen applications.

Following the explanation of Ortt, the large-scale diffusion can be seen as the diffusion of a multi-purpose product for many customer groups instead of the diffusion of specific niche products per customer group. The terms sales take-off and start of large-scale diffusion will be used interchangeably in this master thesis for the concept mentioned above.

1.4 Scientific relevance

Rogers's traditional innovation diffusion model describes a smooth increase in market share similar to a logistic function. Many other scientists agree that the shape of such a diffusion curve resembles a flawless s-shaped curve (Chandrasekaran & Tellis, 2007). Likewise, Tushman et al. (1997) described the technology cycle. The theory explains how a new technology moves from technology discontinuity to a technological substitution, subsequently to the dominant design in the market, followed by incremental changes until a new innovation enters the market. Thus, the model describes well how innovations move through different stages in the market.

However, in many cases, diffusion does not happen as smoothly as expected in reality, especially not in the early diffusion period. Ortt (2010) names the time between invention and large-scale production the pre-diffusion phase in which variations of the innovation are used in niche markets. During this pre-diffusion phase, Ortt and Kamp (forthcoming) describe 14 factors hindering large-scale diffusion. The 14 factors comprise economic and socio-cultural aspects but also extend the theory to include but are not limited to knowledge-driven, product-driven, and institutional aspects. If the 14 factors are resolved, a saddle is avoided, as seen in Figure 4, and innovation will diffuse widely.

In comparison to that, Peres et al. (2010) explain a similar phenomenon characterized by a sudden take-off resulting shortly in a saddle. They explain the reason for the sudden take-off by a reduction of the price, making the product accessible to many users and justifying the risk of new product purchase. The subsequent saddle is explained by technological change, small economic recessions, and the heterogeneity of buyers.

Although both models describe the early period well, however, in two different ways, the models and their factors do not work as a predictive indicator for an upcoming large-scale diffusion of a radically new high-tech innovation. Instead, the models and their factors are too superficially and general. As a result, a definite forecast when an innovation diffuses is not possible. Therefore, this master thesis will explore different scientific branches and develop predictive indicators that forecast the time point of large-scale diffusion.

The literature review in Section 3.2 will show that many predictive models to forecast the diffusion already exist in the scientific branch of “predictive diffusion models.” However, to summarize the chapter's findings, the models do not predict well the early period of diffusion or depend on disclosed data sources. Other branches close to the selected may also deliver answers to the fourth sub research question, such as the branch of “dominant design.” However, they may not be as far developed as the models and indicators presented in the literature review. For example, indicators from the “dominant design” field may observe a sales take-off but not predict a sales take-off.

Concluding this, research is needed with an aim on the early period of diffusion of new innovations, its forecasting techniques, and their predictive indicators. This master thesis will add to the existing literature and open a new field of large-scale diffusion prediction by:

- Designing a research methodology to derive indicators and select them deliberately
- Developing criteria to evaluate predictive indicators
- Giving an overview of relevant forecasting techniques
- Describing characteristics, advantages, and disadvantages of the forecasting techniques
- Guiding researchers and practitioners towards a forecasting technique and its indicators based upon a forecasting approach incorporating hybrid approaches of forecasting techniques
- Deriving and evaluating independent variables predicting the start of large-scale diffusion

The summary of the scientific contribution leads to the managerial relevance of the research due to the monetary reward for companies entering the market at the right moment.

1.5 Practical relevance

This research of evaluating, defining, and explaining forecasting techniques and their indicators predicting upcoming large-scale diffusion of radically new high-tech products has high practical relevance. As mentioned before, companies that enter the market shortly before the diffusion of a product are usually widely successful.

It is of high value for companies to determine the time point of large-scale diffusion of an innovation in their industry. Subsequently, they can select the right moment to start their development and production process based on their experience, time-to-market, and other scientific findings. Finding the right time point will decrease the financial burden of a company entering too early or too late into a market with their product.

However, due to the explorative nature and novelty of the research topic, more research is needed to be able actually to predict the upcoming start of diffusion. Hence, the practical application of the research is limited. As explained in Section 7.3, a straightforward prediction is not possible in the current version of this research. The forecasting approach developed in this thesis will guide a user towards a forecasting technique applicable to large-scale diffusion prediction. Afterwards, a list of indicators is recommended as a starting point for further research. In so far, these indicators predict in detail, and if they work only in combination must be explored afterwards.

1.6 Thesis structure

In Chapter 2, the research methodology to answer the research questions will be developed and explained. For selecting the methods, various alternatives to collect, select and validate the data will be evaluated. Chapter 3 will give a theoretical background to the master thesis and explore the scientific branches. The chapter starts by reviewing forecasting techniques. Afterwards, six different scientific branches to find and derive the indicators will be explored. In the analysis chapter, Chapter 4, criteria to assess the indicators will be developed, discussed and selected. Subsequently, the criteria will be used to rate the derived indicators. A sensitivity analysis will be performed to find the best selection mechanism for the final selection of indicators. This selection mechanism will be used to create the final list of predictive indicators. Chapter 5 will focus entirely on developing and describing the forecasting approach combining the forecasting techniques and their recommended indicators. After the approach has been presented, the findings will be validated in Chapter 6. Finally, in Chapter 7, the work will be discussed and concluded by answering the research questions, discussing the work and presenting opportunities for future research.

2 Research Methodology

The objective of this master thesis is to answer the main research question in a sound and scientific manner. For this, an elaborated strategy is required to avoid errors in the research design. Furthermore, the research topic of this master thesis is rather unique as hardly any research has been done in the same field (compare Section 1.4). Therefore, a new research methodology is required to answer the main research question (see SRQ3 in Section 1.1).

2.1 Methods for data collection, selection, and validation

In the following section, the methodology for the data collection, data analysis, and data validation of the thesis is presented. First, a variety of alternatives for each research step are discussed. Afterwards, the decision for one of the alternatives is justified given the focus and fit to the topic.

2.1.1 Data collection

The aim of the data collection process in this thesis is to find qualitative information that can be further analysed later. Therefore, for this research, three kinds of information are required:

1. Forecasting techniques
2. Indicators that other researchers have already used for similar forecasting models
3. Theoretical and practical mechanisms which describe a behaviour or situation of an innovation, an innovating firm or its environment

The first kind of information will be derived and researched based on a literature review. Forecasting techniques are widely used and have been researched quite extensively. Hence, a literature review and a subsequent analysis are sufficient to overview and discuss the various techniques.

Indicators in combination with forecasting techniques have not been connected adequately so far. Therefore, a more elaborated and explorative data collection procedure is required for the other two kinds of information.

To achieve a holistic and systematic assessment of the situation in which an innovation is placed before the start of large-scale diffusion, the data collection cube shown in Figure 5 has been created. A variety of perspectives are used to achieve the holistic view. This holistic viewpoint is required to include all kinds of mechanisms from various perspectives. Only by considering many perspectives it can be ensured that all indicators assessing the environment around an innovation and the innovation itself are found. The perspectives can be divided into (i) indicator type, (ii) indicator class, and (iii) indicator source. Each perspective functions as a nominal scale, after which the indicator will be classified.

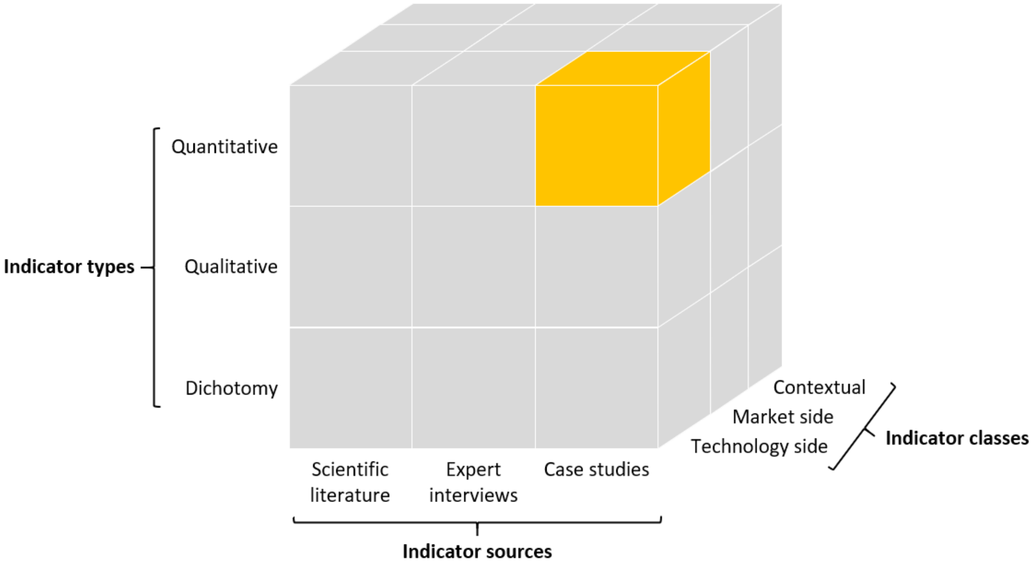


Figure 5: Data collection cube

After defining the research gap in the systematic literature review, the cube was developed because first insights were needed to create an adequate data collection method. Therefore, the cube's indicator types and indicator classes have been based upon the classifications and findings in Section 3.2 and extended further.

Indicator types

The systematic literature review (see Section 3.2) has shown that current predictors are primarily quantitative. However, these currently existing indicators only predict well at the maximal turning point[1] of the diffusion curve. Therefore, various perspectives are necessary to observe the developments of an innovation, the environment around an innovation, and its innovating firm holistically.

The indicator types will be extended by the inclusion of qualitative and dichotomous variables. While quantitative indicators are mostly free from bias, they do not carry well more abstract concepts such as the overall optimism of the industry regarding an innovation. Additionally, dichotomous indicators might be relevant for the diffusion, such as an accident or unforeseen event. Nevertheless, one should be careful to use qualitative and dichotomous indicators as they might be applied differently depending on someone's understanding or personality.

Indicator classes

An extension to the indicator classes is contextual variables besides the already used technology and market variables in the systematic literature review (see Section 3.2.6). For the master thesis, I define the three concepts as shown in Figure 6.

[1] The maximal turning point is reached when an innovation diffusion changes from the early majority customer group to the late majority group.

Technology indicators concern foremost the technology used for the innovation. For example, typical technology indicators are the number of patents, production capacity, and product performance.

Market indicators emerge from an interplay between the supply and demand sides. This interplay includes apparent indicators such as product price but also the number of firms, mentions in the popular press, and the number of trade fair presentations. While the last two examples might also be categorized as a technology indicator, they emphasize the demand and supply relationship established via media channels or trade fair shows. It is essential to mention that the market extends in two ways: upstream and downstream the value chain.

Contextual indicators emerge from the overall setting of an innovation. They describe the institutional setting, the context in which an innovation will enter the mass market, and further influential barriers hindering or promoting the diffusion. Compared to the market indicators, contextual indicators are less dominated by customer behaviour but rather influenced by institutions like governments, cultures, and unforeseen events.

Figure 6: Definition of technology, market, and contextual indicators

I distinguished supply, demand, and contextual indicators in an earlier version of the data collection cube. However, the definition of the perspectives was too ambiguous because some indicators measured a construct resulting from an interplay of supply and demand forces. To overcome this ambiguity, supply and demand factors have been summarized in the market perspective. While truly technological constructs, which earlier have been seen from a supply perspective, are now categorized in their separate perspective.

Indicator sources

The indicator sources are highly relevant and determining for the collection of the potential forecasting indicators. They decide from which knowledge source indicators are taken or derived. Three main indicator sources[2] are available:

1. Scientific literature
2. Expert interviews
3. Case studies

The indicator source scientific literature can be further divided into two collection procedures. On the one hand, a few diffusion models already exist (see Section 3.2). Therefore, indicators that have been used in these models will be directly added to the list of observing indicators. On the other hand,

[2] Backcasting might be added to the list of indicator sources. However, the imagination of a future situation might create bias and is therefore not recommended.

indicators can also be derived from sound mechanisms and theories explained in the scientific literature.

Interviews with experts of innovations and diffusion are another indicator source. Practitioners and researchers in the field can report from their work and observations. These observations can then result in derived indicators. Likewise, case studies can be used as the third source of indicators. Case studies can be read or developed while simultaneously observing the mechanisms described during the diffusion, which results in derived indicators.

However, the choice has been made against the indicator sources expert interviews and case studies. This is because the prospective insights gained from the two sources have been evaluated as too marginal for the effort needed to prepare and carry out the data collection in the limited time available for the master thesis. Nevertheless, interviews will be used in the data analysis and validation as they provide great insights for narrowing down and validating the research.

2.1.2 Procedure for data analysis & selection

For the data analysis and indicator selection, a stepwise approach will be used. Three steps will be used to narrow the field down and to conserve the most potential indicators.

Selection of scientific branches

First, scientific branches will be selected that describe mechanisms that can influence the upcoming start of large-scale diffusion of a radically new high-tech innovation. For this purpose, the following scientific branches have been selected:

- Diffusion forecasting
- Macroenvironment
- Dominant design
- Crossing the chasm
- Disruptive innovation
- Pre-diffusion

Why these branches have been selected and to what degree they contribute towards the research objective will be discussed below.

The diffusion forecasting branch is the only scientific field providing applicable frameworks for diffusion prediction. Although the forecasting models do not necessarily predict the upcoming start of diffusion, a literature review is necessary to understand the existing forecasting models and their indicators. It might be possible that some indicators from the diffusion forecasting branch also predict the upcoming start of large-scale diffusion. Therefore, a systematic literature review will be performed to find all existing indicators incorporated into other forecasting models. If the diffusion forecasting indicators predict will be checked by entering the data selection funnel described below.

Next, the macroenvironment branch has been selected to learn from the holistic assessment researchers, especially Kotler, have developed. The branch classifies uncontrollable forces an innovating firm is confronted with, which might hamper large-scale diffusion. Hence, the macroenvironment branch is needed to include a comprehensive perspective of mechanisms happening around an innovating firm into the analysis.

The dominant design branch has been included in the analysis for rather obvious reasons. A dominant design is usually established after the large-scale diffusion. However, forces and mechanisms which lead to a dominant design might also be relevant to predict the start of large-scale diffusion. For example, a high certainty over customer requirements is needed to develop a design that matches the customers' needs. This design could potentially become the dominant design in the market later. However, following a similar logic, more customers will adopt a new product innovation that signals the upcoming large-scale diffusion if a design fits the customer requirements.

Crossing the chasm means closing the gap between the early adopters and the early majority. At first sight, the corresponding scientific branch seems highly relevant for the research because the start of large-scale diffusion falls into the same timeframe. However, as the literature review will show, only limited findings of the branch apply to the research. The crossing the chasm branch has a strong focus on customer groups. These topics are less relevant for the research due to a significant hindsight bias defining the customer groups.

The disruptive innovation branch is another scientific field that only overlaps partly with this thesis's research objective. This thesis focuses on radically new high-tech innovations. In contrast, the branch in focus only looks at a fraction of these innovations by defining disruptive innovations in a more granular terminology. Many disruptive innovations might be radically new high-tech innovations. In contrast, only a few radically new high-tech innovations also classify as disruptive innovations. Therefore, the literature review will show that the scientific field is too narrowly defined for this master thesis. As a result, only a few findings are applicable to derive indicators.

Compared to the other scientific branches, the pre-diffusion branch has one of the strongest overlaps with the research objective. The pre-diffusion branch offers a framework covering the environment around an innovating firm, as well as the company and product in focus. The framework has been developed based on other scientific literature. It provides a unique combination of 14 factors that influence developments during the pre-diffusion phase before large-scale diffusion. It is assumed that the factors of the pre-diffusion branch are complete because the model has been developed throughout various years in different iterations based upon many different sources (see Section 3.7 for more insights).

It can be seen that the pre-diffusion, diffusion forecasting, macroenvironment, and dominant design branch have strong relevance for the topic. On the other hand, the crossing the chasm and disruptive innovation branches are already less relevant for the research due to their specific focus. Other branches were not found to be relevant enough for the research objective or too narrowly defined. For example, the branches of sustainable innovations, technology assessment and technology readiness levels have not been included in the literature review.

The sustainable innovations branch, with its work by Geels, only analyses and discusses sustainable innovations. The scientific branch is too narrowly defined in terms of applicable innovations. This issue already occurred with the disruptive innovation branch in which certain findings did not apply because the radically new high-tech innovations are defined more broadly, including more technologies, than the disruptive innovations.

The technology assessment[3] branch measures the effect of innovations on society before the diffusion. However, the direct influence of these effects on the actual diffusion was not evident. Hence, the scientific branch has been excluded from the literature review because of the missing immediate connection to large-scale diffusion forecasting.

Lastly, the branch of technology readiness levels measures how mature a technology is on a scale from one to nine. Space agencies and other institutions often use this information to evaluate a technology's readiness during the acquisition phase and to aid the decision-making process of buying a company or product (ESA, 2021). A technology's readiness influences the diffusion of a product. Especially a product's performance and its derived value is a determining factor in convincing a customer to buy a product. However, a technology's readiness is not everything to enter the mass market. Other branches, such as the pre-diffusion branch, already measure a technology's performance besides 13 other factors. The technology readiness level branch has been excluded from the literature review due to its possibly marginal influence on the research findings and limited time for this master thesis. Other branches were found to cover better the entire environment around and innovation and its innovating firm.

Nevertheless, it is advisable to analyse the three scientific branches (sustainable innovations, technology assessment, and technology readiness levels) as future research (see Section 7.3). What exactly has been concluded from the literature reviews can be found in Section 3.8.

Pre-selection of indicators

Indicators will be collected or derived from these scientific branches. During the literature reviews, a pre-selection is made before indicators will be collected in a list of potential indicators. Indicators will only be included in the list of observing indicators if they fulfil the following criteria:

- Measure constructs related to the timeliness of innovation diffusion
- Reflect on changing dynamics of the innovation or its environment over a time series of data points

The prediction of a timepoint, in fact, the start of large-scale diffusion, is only possible if the construct is related to the timeliness of diffusion and its value changes during the time between invention and the start of diffusion. If the measured construct of an indicator improves over time, making the diffusion more likely, a forecasting technique can evaluate these incremental changes and predict the timepoint of diffusion. Indicators which measure a static situation since invention are not very useful

[3] Definition Technology assessment: "Technology assessment (TA) refers to the early identification and assessment of eventual impacts of technological change and applications, as a service to policy making and decision making more generally." (Rip, 2015)

for the prediction. Changes do not exist, making it impossible to predict a time point based on a selection of static indicators.

Final selection of indicators

Lastly, more elaborated criteria will be used to classify and pick the most promising indicators. I will assess the majority of the criteria. However, experts in an interview will assess the most critical criterion if an indicator predicts or not. Only if the experts gave their green light for an indicator, the indicators would be incorporated into the forecasting approach. More information regarding this validation step will be given in the next section.

While a simple pass/non-pass assessment will be made for the first two steps, the indicators that reached the third step will be assessed based on a five-point itemized rating scale. The itemized rating scale allows the summing of results per indicator because of its interval scale (Sekaran & Bougie, 2016). In addition, the scale is balanced, offering a neutral point. I decided to use five points per scale to allow for a nuanced assessment of the criteria without creating too much choice in the assessment. Furthermore, research has shown that a scale with more than five points does not improve the reliability of the assessment. The criteria for this assessment will be developed, discussed, and selected in Section 4.1. A preview of the whole data selection funnel and its criteria can be seen in Figure 7.

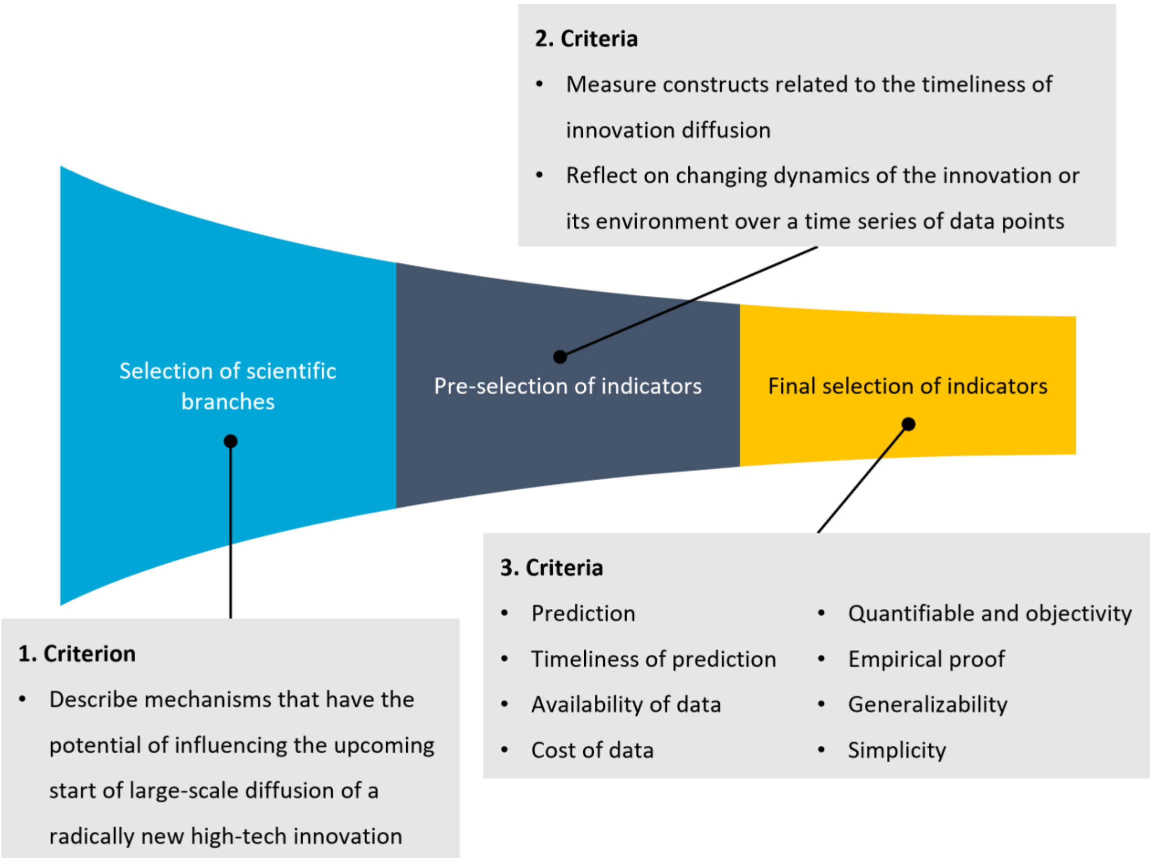


Figure 7: Data selection funnel

After evaluating the criteria in the third selection step, a sensitivity analysis will be performed to improve the robustness of the selection process. Various approaches to calculate an overall value will be presented in Section 4.3.1. Results of the selection mechanisms will be compared to see variances. Comparing the results will ensure that an indicator is not arbitrarily excluded by one of the selection mechanisms. If somewhat similar results occur among the selection mechanism, it is ensured that indicators are excluded because of their bad ratings but not because of a selection error. Then, the theoretically most sound selection mechanisms will narrow down the indicators towards the most potential ones.

Based on the selected indicators and the discussion of forecasting techniques, an approach will be developed, guiding a user towards an advised forecasting technique and its respective indicators. How the approach will be validated finally is explained in the next section.

2.1.3 Data validation

Especially qualitative research has been criticized for its lack of rigour and validity in the past (Noble & Smith, 2015). To ensure a sound research design and execution, various measures that Noble & Smith described have been implemented.

Completeness of the indicators

First, the data collection cube has been presented to base the results on various perspectives through data triangulation. Although not the complete cube will be used because the indicators sources are restricted to scientific literature, various scientific branches are covered. Each branch embodies a perspective on its own which ensures a more comprehensive set of indicators.

To verify that the indicators, which have been derived and collected from the literature reviews, assess the innovation and environment around an innovating firm holistically, the indicators will be classified according to the 14 factors of the pre-diffusion branch. Earlier in this chapter, it has already been argued that the framework of the pre-diffusion branch is assumed to be complete. Therefore, the factors of the framework fit well to see if indicators for each perspective have been found, indicating the completeness of the indicators. This verification step will be repeated after selecting indicators to see if the remaining indicators still assess the research objective holistically.

Various respondents to evaluate the indicators

Secondly, a stepwise data section funnel is utilized to make the selection criteria transparent and clear. Findings from each step will be made clear in the corresponding chapters and allow other researchers to retrace the decisions. Moreover, besides functional criteria such as availability and cost of data, the empirical proof of the indicators will be measured. This further increases the overall validity of the indicators and the final forecasting approach.

Furthermore, the assessment of the criteria will be split. Selection criteria will be assessed by me, while the criterion prediction will be assessed by three experienced researchers (see Table 11 for the background and expertise of the researchers).

The assessment happens based on a fully structured interview with closed questions. Compared to a semi-structured or open interview, a fully structured interview asks the same questions to each participant. This strict setup focuses on the rating and allows to compare the results given by each respondent.

Additionally, the structured interviews facilitate the respondent validation reducing my personal bias towards preferred indicators. The criterion *Prediction* acts as an external scientific quality gate due to the criterion's importance in the selection mechanism (compare alternatives of selection mechanisms in Section 4.3.1).

Exploring opinions or indicators, something an open or semi-structured interview would offer, is not required at this step anymore. The exploration phase of collecting indicators has already been finalized at the end of the literature reviews. An open or semi-structured interview would shift the attention to the exploration, possibly altering the focus of this method: validating the research and rating the indicators.

Final validation

Lastly, a final check of the findings is required. Although sound scientific methods will be applied to the research, only a final check can ensure validity and applicability. Therefore, the final check should be as close as possible to the practical application of the prediction approach. For this final check, three kinds of validation methods are possible:

- Actual application of the prediction approach for a variety of case studies
- Demo case study
- Expert interviews

While the actual application of the prediction approach is closer to reality, the time consumption of the validation is too high for a master thesis. It would take several weeks to familiarize myself with case studies and collect the indicators' data. Therefore, the next best method has been selected in a combination of the second and third options. For the final check, a demo case study will be prepared and presented to external participants. This method also provides advantages which will be explained below.

Compared to the actual application, expert interviews have the advantage of including an external perspective based upon years of experience in the field. Participants should be working in the industry to include the perspective of applicability. These expert interviews would also contrast to the earlier, more scientific expert interviews about the indicators. While in the first external validation, the scientific background of the indicators was relevant, in the final check, applicability and overall validity of the forecasting approach on green hydrogen are in focus.

For the validation interviews, a semi-structured interview setup will be used. On the one hand, the experts should assess if certain decisions and conclusion match their experience. For this purpose, closed questions will be used to provide comparability among the respondents. On the other hand, the participants should also assess the practicability of the research and if it incorporates all relevant indicators. This completeness will be checked by using open questions, allowing the participants to share their experiences.

The next section will give an overview of the research framework based upon the consideration discussed in the previous sections.

2.2 Research framework and strategy

As Section 2.1 has already suggested, a unique research framework is required to answer the research questions. Figure 8 shows the research framework of the master thesis incorporating the selected methods from the previous section. The methods have been ordered according to their place in the chapters of the thesis.

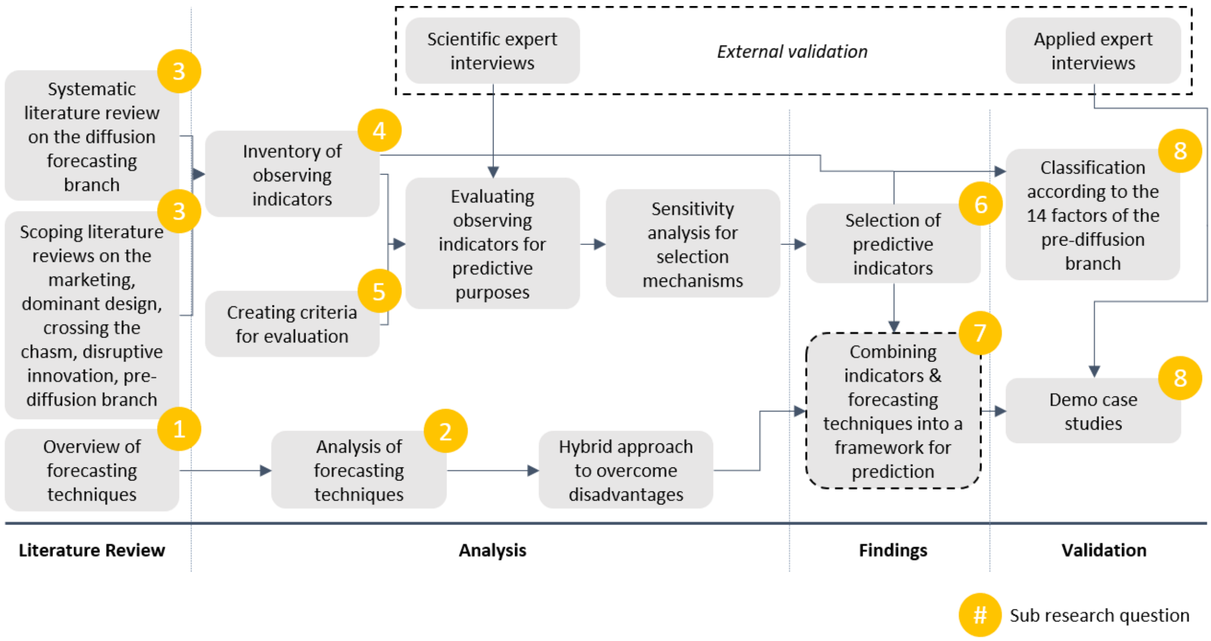


Figure 8: Research framework

Literature reviews

The literature reviews of the forecasting techniques and different scientific branches will answer SRQ1 and SRQ3, respectively. First, information found about the forecasting techniques will be analysed and used to answer SRQ2. Then a hybrid approach will be used to overcome the disadvantages of each forecasting technique.

Analysis & Findings

Alongside, an inventory of the observing indicators will be made to answer SRQ4. Indicators found in the perspectives, which can observe and reflect on changes, do not instantly predict the start of diffusion. This differentiation is crucial for the following analysis. However, it is expected that some of the observing indicators also predict the start of diffusion. After that, criteria to evaluate the indicators will be developed for the SRQ5. Partly the criteria will be assessed by scientific experts. To finally select the predictive indicators, a sensitivity analysis will be performed to increase the robustness of the selection mechanism. The selection mechanism results in the final selection of indicators answering SRQ6. Finally, to combine the indicators and the forecasting techniques, a framework for prediction will be designed, answering SRQ7.

Validation

Lastly, to validate the research, two demo cases will be solved to apply the research (SRQ8). Additionally, the identified and selected indicators will be compared to the 14 factors of the pre-diffusion branch. This comparison will reveal if the selected indicators predict the large-scale diffusion holistically. Next to it, experts in the field are interviewed to confirm or reject the findings.

3 Literature Review

In this literature review, the forecasting techniques and mechanisms from six different scientific branches will be explored. First, an overview will be given and appropriate methods explained in more detail for the forecasting techniques. At the end of the section, the forecasting techniques will be discussed and compared.

A different method will be used for the six scientific branches to derive the indicators because a more in-depth analysis is required to find the mechanisms influencing the pre-diffusion phase. Generally, two types of literature reviews are possible: a systematic and scoping literature review. A systematic literature review is based upon a keyword search and analyses all articles which have been found. In comparison to that, a scoping literature review only focuses on the most popular articles and has, therefore, far less depth than a systematic literature review. However, a scoping literature review also requires less time.

For the diffusion forecasting branch, a systematic literature review is required. A variety of models has been developed, and indicators might also work for the pre-diffusion phase. Hence, an in-depth analysis and collection of the indicators are needed.

The other five scientific branches do not require such an in-depth approach. Of interest are the mechanisms that researchers describe in each branch and their relation to the pre-diffusion phase. Most of the mechanisms are described in a few popular articles. Details and minor variations in these mechanisms are not required as the overall concept of the scientific branches is in interest to derive the indicators. Hence, the key concepts will be explained first based upon the most popular articles. Then the knowledge will be used to derive indicators emerging from the discussed disciplines.

3.1 Forecasting techniques

Before introducing models and theories, I will describe four classes and their forecasting techniques in the following sections. The classes of forecasting techniques have been adapted from the classifications by Kahn (2010) and Mas-Machuca et al. (2014). Additionally, findings from Cho (2013) and Chambers et al. (1971) have been integrated. However, for the purpose of the thesis, only relevant forecasting techniques will be presented. The criteria to select the forecasting techniques are as following:

- Can theoretically forecast the time of large-scale diffusion
- Applicable to radically new high-tech innovations
- Based upon a given set of indicators to achieve reproducible results

To get it started, I will begin by introducing (i) judgemental techniques. Following that, (ii) time series & regression modelling techniques and (iii) consumer research techniques will be described. Lastly, more modern techniques of the category (iv) machine learning techniques will be presented.

3.1.1 Judgemental techniques

Judgemental forecasting techniques base their prediction on qualitative expert opinions (Kahn, 2010). Especially for radically new high-tech innovations, judgemental methods can be more insightful than quantitative techniques (Mas-Machuca et al., 2014). Radically new high-tech innovations might provide limited quantitative data, which creates the necessity to rely on judgements by experts. Moreover, this class's methods are more aware of threats and potentials outside the norm (Cho, 2013). Nevertheless, judgemental techniques may introduce bias into the forecast based on the preferences of the participating experts.

Three judgemental techniques have been found to comply with the criteria as mentioned earlier: (i) Delphi method, (ii) assumption-based modelling, and (iii) analogous forecasting. The techniques will be explained and discussed in the following sections.

Delphi method

To apply the Delphi method, information and opinions are collected through various interview rounds (Kahn, 2010). The interviews are structured and anonymous. The interviews will be conducted in a structured way based upon indicators to provide a systematic approach.

In each round, a conclusion from the prior collected data is presented to the respondents, which is subsequently further refined by all respondents separately. Usually, the Delphi method starts by collecting the numerical value per indicator (Mas-Machuca et al., 2014). The method aims to question more than one expert without applying the effects of social pressure.

Assumption-based modelling

The assumption-based modelling is, to some extent, like the Delphi method. A market environment, broken down into indicators, is assessed by experts (Kahn, 2010). However, the method does not focus on reducing pressures among experts as much as the Delphi method.

It is possible to conduct the method in two ways. Experts do the assessment separately in the first method, and an average value per indicator is calculated. In the alternative method, experts do the assessment discussion-based and agree on one value per indicator.

Analogous forecasting

Analogous forecasting is a method which usually classifies as quantitative (Kahn, 2010). However, due to the focus on radically new high-tech innovations, the number of analogous technologies is limited. The innovations are defined as discontinuous and apparent similarities to other technologies do not always exist. However, experts might find and describe an older technology as somewhat similar or closely related in its characteristics, including its market environment. To define technologies as analogous, both technologies should fulfil the following requirements:

- Similar market, industry, and customers
- Similar stage in the pattern (compare Figure 16 in Section 4.1.3)
- Similar indicators hampering the diffusion (including qualitative and quantitative indicators)

The quantitative method transforms into a more judgemental approach. If an older technology is seen as comparable, sales data can be used and adapted to the current situation.

However, the method is not superior in its reliability compared to truly quantitative or qualitative methods. Nevertheless, analogous forecasting might be a viable option if time and costs constraints apply.

Forecasting techniques that have not been included in the analysis are the Jury of executive opinion and Sales force composite (Kahn, 2010). Both methods orient themselves at an organizational structure of a company and work top-down or bottom-up, respectively. The prediction of large-scale diffusion of an innovation does not fit in such a scheme. Indicators can hardly be integrated into such a technique in which aggregated forecasts are taken one level up or down, respectively, to start a new assumption. Experts with a track record of knowledge and experience about the innovation are required to judge the indicators and not employees from different levels.

3.1.2 Time series & regression modelling techniques

Time series analysis usually uses past sales data of continuous innovations to find patterns that predict future behaviour (Cho, 2013; Kahn, 2010). However, in the case of predicting the start of large-scale diffusion, sales data is scarce or not available. Additionally, no data is available due to the discontinuous nature of the innovations in focus. Therefore, indicators must be used that do not reflect on sales data but forecast mechanisms that affect a technology trajectory and, subsequently, the sales of a product. Due to this, famous models such as the Bass model, Fisher-Pry model or Technology Forecasting Data Envelopment Analysis are not applicable for the sales take-off prediction.

Techniques in this forecasting class usually create an S-shaped curve anticipating the start of diffusion (Cho, 2013). However, the models are also known to be naïve as they expect a standardized behaviour. Therefore, most time series and regression models are found to be not relevant for discontinuous innovations with an exception to the following three methods, which will be presented in the following sections: (i) Cox regression, (ii) Logistic regression, and (iii) Gompertz regression.

Cox regression

The Cox regression is a different kind of method than the other two regression methods. The Cox regression is a proportional hazard model calculating the survival time of an object based on independent variables (Bender et al., 2005; Cox, 1972). Independent variables can be quantitative or dichotomous. The regression method is often used for medical applications forecasting the time of mortality of infected patients. However, the Cox regression also became famous in the diffusion forecasting branch (compare Section 3.2.6 & Mas-Machuca et al., 2014). Here, the event to be predicted is the time point of take-off.

Logistic and Gompertz regression

The other two methods, the Logistic regression and Gompertz regression, use a different approach. By fitting data to an S-shaped curve, the time of steep incline (take-off time) can be calculated. Although it was found that the Gompertz regression outperforms the Logistic regression in the time before the take-off, neither of the two models actually predicted the start of diffusion (Wu & Chu, 2010). The Gompertz curve had a slightly better fit with the actual diffusion data. However, both models failed to predict the steep incline of sales.

Nevertheless, the data used for the analysis by Wu & Chu (2010) is based on the sales numbers per year. This data will not be used for the indicators derived in the later sections of the thesis. As the indicator approach in this master thesis is unique compared to most diffusion models, relevant comparisons of regression models do not exist. Therefore, the two methods will still be included.

Many quantitative techniques have not been included in the analysis. For example, all methods based on trend lines or averages are excluded. Such forecasting techniques require a history of sales data of the innovation in focus. However, radically new high-tech innovations have not reached the market yet. Therefore, historical sales data for the innovation is not available.

3.1.3 Consumer research techniques

Consumer research techniques forecast based on consumer data (Kahn, 2010). Mainly new products in established product categories are tested (Mas-Machuca et al., 2014). However, the results are often short-term, and the reliability regarding radically new high-tech innovations is limited. Furthermore, customers are usually confronted with enhancement, social desirability or other forms of bias (D. Elsbach & Stigliani, 2020; Fisher, 1993; Zhao & Meyer, 2003). Therefore, no consumer research technique is directly applicable to forecast the start of diffusion for radically new high-tech innovations.

However, models could be possible in which consumer indicators are fed into other forecasting techniques. For example, the short-term data would indicate the customer acceptance of new innovations. Combined with other indicators, this information could better describe the environment in which an innovation diffuses.

3.1.4 Machine learning techniques

The forecasting class of machine learning techniques is relatively new, but early developments have shown superior forecasting performance (Mas-Machuca et al., 2014; Raza & Khosravi, 2015). Additionally, machine learning techniques tend to improve while using them. However, for the purpose of classification, machine learning techniques are not always distinctive and overlapping among each other or even between forecasting classes. However, a technique that qualifies for predicting the start of large-scale diffusion is artificial neural networks because the method complies with the previously mentioned criteria.

Artificial neural networks

Artificial neural networks can find and understand patterns in time series data (Kahn, 2010). However, such an analysis can be time-consuming. On the other hand, patterns in large data sets can be made visible, which would not have been found by hand.

A neural network works similarly to a brain (Chawla et al., 2019). Nodes on the input layer take signals from indicators. In the hidden layers, signals are processed by connecting nodes. Finally, an output or decision is given through the output layer in the network. The connection of the nodes will get refined by using training data. This trainings data consists of input as well as output data. By understanding the input and its corresponding output, the neural network will get more sound.

Neural networks can be categorized according to their learning process and network architecture (Raza & Khosravi, 2015). The learning process is divided into supervised learning and unsupervised learning (see Figure 9). The former tries to use the training data and its expected output value to reduce errors. The neural network tries to reach an output value close enough to the original value given an error threshold during the training process. On the contrary, the unsupervised learning technique does not have a given output value in the training data. Instead, the network tries to adjust itself based on patterns recognized in the input data.

Feed-forward neural networks have a network architecture somewhat linearly. Information flows from the input to the output layer through various hidden layers depend on the neural network setup. On the other hand, data is fed back into a previous layer in a feedback neural network, allowing data to flow bidirectionally. Thus, feedback neural networks are appropriate for dynamic and time-varying research problems (Raza & Khosravi, 2015).

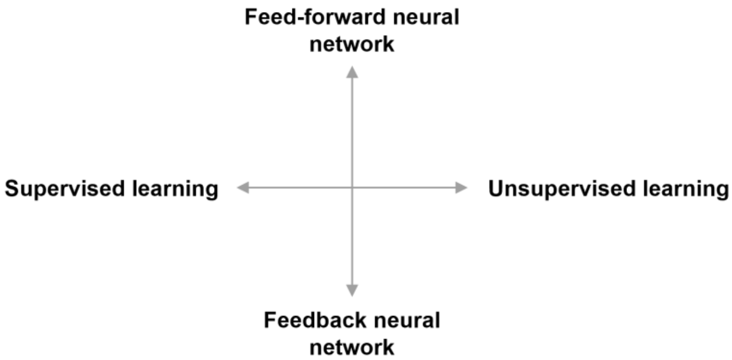


Figure 9: Classification of neural networks

To unfold a neural network's entire potential large quantity of data are required. This data includes information from many different independent variables but also data from many different case studies. Especially if the variables are complex in their relations, machine learning algorithms can find patterns more reliable and quicker than humans. However, much time is needed to collect the data. Therefore, neural networks are not always economical or for any kind of situation useful.

3.1.5 Discussion of the forecasting techniques

In the earlier sections, forecasting techniques that are relevant to the research have been introduced. However, each forecasting technique is unique and distinguishes well from the other methods. In this section, the forecasting techniques will be discussed and compared with each other. All three regression methods (Cox, Logistic, and Gompertz regression) will be assessed combined. Selecting the correct regression models is case dependent (Wu & Chu, 2010) and not part of the research. An overview of the comparison can be seen in Table 1.

Table 1: Assessment of forecasting techniques

Criteria	Delphi method	Assumption-based modelling	Analogous forecasting	Time series & regression models[4]	Artificial neural networks
Reliability	medium	low	low	medium	high
Ease of operation	medium	high	high	medium	low
Time consumption	medium	low	low	high	very high
Industry experts necessarily required	yes	yes	yes	no	no[5]
Prevention from bias	medium	low	low	high	high
Variety of case studies required	no	no	high	no	very high[6]
Variety of independent variables required	medium	medium	medium	medium	high
Historical data points per independent variable	no	no	no	yes	yes

The least complex method is assumption-based modelling. Several experts, depending on availability and desired reliability, rate pre-defined indicators. As described before, the rating of indicators can happen by each expert separately or together. While the first method reduces the influence of a strongly opinionated or highly valued expert, it might also lead to significant deviations between the ratings because of different knowledge and information availability. These deviations in the assumption-based modelling result in a low rating for the criterion bias prevention. Nevertheless, assumptions-based modelling does not consume much time.

The Delphi method uses information-sharing and anonymous rating rounds to counteract the two issues of assumption-based modelling. Information and knowledge of each expert are shared with all other experts after each round of ratings. This method tries to reduce the bias emerging from strong personalities while simultaneously creating an environment of knowledge equality. In addition, the anonymous round-based rating of indicators increases the reliability of the judgemental technique compared to the assumption-based modelling.

The last judgemental approach, analogous forecasting, uses a different approach than the two forecasting techniques before. A match between a historical diffusion pattern and the technology in focus is made based on indicators. Similarly to assumption-based modelling, analogous forecasting is easy and quick. However, it requires an extensive database of radically new high-tech innovations to

[4] Cox, Gompertz, and Logistic regression have been summarized to one category.
[5] A data science expert is required for the setup of the method, not for the judgment of the indicators.
[6] Techniques exist to augment the training data for machine learning use cases. However, the reliability of the data must be assessed before using it.

which the technology in focus can be compared and matched. The decision that two technologies match is made by an industry expert. However, no actions are done to minimize bias or errors by the expert during the matching process.

The quantitative models provide better prevention from bias due to minimized human interaction. The most advanced forecasting technique in terms of reliability is the use of artificial neural networks. Although they require vast amounts of data and implementation time is very high, in some cases, neural networks are the best solution due to their superior pattern recognition. Nevertheless, it should not be forgotten that artificial neural networks require trained personnel for the setup and maintenance.

Another class of methods that limits bias while at the same time keeping the time consumption low are the regression models. Although the method does not detect patterns in the indicators' data, historical data for the case in focus is required for the regression analysis. The substantially lower time consumption for the setup of the method goes to the cost of reliability. Yet, the method is more reliable than some of the judgemental methods. Moreover, the method can be implemented by an employee with average analytical skills.

Each method has its unique use case where it is applied best. To guide the decision process for a researcher or employee, a framework will be developed and presented in Chapter 5. This chapter's advantages and disadvantages are further discussed and how the disadvantages can be overcome using a hybrid approach.

Takeaways from the forecasting techniques

Forecasting techniques can be classified into four categories, as seen below. Each category has its characteristics.

Judgemental techniques

- prediction based on qualitative expert opinions
- often introducing bias in the category of radically new high-tech innovations

Consumer research techniques

- forecasting based on consumer experiments
- results are often short-term and not reliable in the category of radically new high-tech innovations

Time series & regression modelling techniques

- primarily based on historical data
- might incorporate judgemental or consumer research data
- some models focus especially on radically new high-tech innovations achieving superior reliability

Machine learning techniques

- can include judgemental or quantitative data
- can handle large quantities of data
- the field of research is relatively new, but early developments show superior forecasting performance

3.2 Systematic literature review: Diffusion forecasting branch

The literature review will be done according to a self-standing, traditional, systematic approach discussed by Jesson et al. (2011). This review aims to explore existing literature and to provide information on existing forecasting models. The journal's quality has been evaluated to solely include high-quality articles incorporating scientific methods in the literature review (see Appendix A: Quality of the systematic literature review).

3.2.1 Search Description and Selection Criteria

The literature review started by assessing scientific papers that I already read for the course "Emerging and Breakthrough Technologies" during my master studies. The course already touched upon innovation management and large-scale diffusion, and the literature built an excellent starting point. The majority of relevant papers of the course were written by the module manager himself, Roland Ortt, who is also one of the supervisors of my thesis project. To kickstart my research, he provided me with two articles by Agarwal and Bayus (2002) and Bayus et al. (2007), who developed one approach to predict an upcoming large-scale diffusion.

Fast I realized that a standard keyword search could not narrow down the articles to a reasonable number. The topic I am researching is diffuse and has a lack of standardized vocabulary. While many scientists refer to the turning point in a sales curve, where a product begins to be widely available in the market, as diffusion (Chandrasekaran & Tellis, 2007), others name it market adoption or sales take-off. The same problem occurred while describing the nature of the product in focus. The product should be based on a high-tech innovation that is radically new to the market. Some scientists preferred to call it a breakthrough innovation, while others used the term disruptive innovation. All keywords are describing, for the case of this literature review, a somewhat similar concept. Therefore, I settled with the in Table 2 mentioned keywords.

Table 2: Keywords and synonyms

Keyword	Synonyms	Search Term
diffusion	market formation, market adoption, take off, takeoff, take-off	*TITLE-ABS-KEY (("diffusion" OR "market formation" OR "market adoption" OR "take off" OR "takeoff" OR "take-off") AND ("innovat*" OR "technolog*" OR "product") AND ("radical*" OR "disrupt*" OR "new" OR "breakthrough" OR "emerging") AND ("factor*" OR "variable*") AND ("forecast*" OR "predict*"))*
innovat*	technolog*, product	
radical*	disrupt*, new, breakthrough, emerging	
factor*	variable*	
forecast*	predict*	

I realized that many articles came from research areas that did not correspond with my desired field. For example, the area of medicine will be excluded from the literature review as the used keywords resulted in entirely different topics. Therefore, I excluded research areas such as medicine, pharmacy, arts, mathematics, environment, earth science by adding the search term shown in Table 3 along with an "AND" operator. Furthermore, I limited the language to English because I am not fluent in reading the small number of Chinese, French, Russian, Croatian, or Portuguese articles showing up in the keyword search.

Table 3: Excluded research areas

(EXCLUDE (SUBJAREA , "CHEM") OR EXCLUDE (SUBJAREA , "MATE") OR EXCLUDE (SUBJAREA , "CENG") OR EXCLUDE (SUBJAREA , "PHYS") OR EXCLUDE (SUBJAREA , "MEDI") OR EXCLUDE (SUBJAREA , "ENER") OR EXCLUDE (SUBJAREA , "ENVI") OR EXCLUDE (SUBJAREA , "BIOC") OR EXCLUDE (SUBJAREA , "EART") OR EXCLUDE (SUBJAREA , "AGRI") OR EXCLUDE (SUBJAREA , "PHAR") OR EXCLUDE (SUBJAREA , "ARTS") OR EXCLUDE (SUBJAREA , "NURS") OR EXCLUDE (SUBJAREA , "HEAL") OR EXCLUDE (SUBJAREA , "IMMU") OR EXCLUDE (SUBJAREA , "DENT")) AND (LIMIT-TO (LANGUAGE , "English"))

This further exclusion of articles resulted in 354 articles on Scopus on 20.12.2020. I was not able to further narrow down the field by a keyword search. Hence I decided to apply the "scan-skim-understand" reading technique from Jesson et al. (2011). After the keyword search, I narrowed down the number of articles by scanning the title and abstract.

To avoid missing important articles, I relied on an article's reference list, the "cited by" section on Scopus, and the "related documents" section on Scopus suggesting articles based on the reference list. This method helped me to find especially new articles and review articles giving an overview. Furthermore, it also helped me to familiarize myself with the research area by getting to know essential authors, concepts, and methods. I looked out for diffusion models having a forecasting approach instead of an observational nature. Furthermore, I focused on radically new high-tech innovations and consumer durables. Consumer durables are products used by consumers over a long period (Merriam-Webster, 2021a). This product category has been included in the review besides the radically new high-tech innovations because many models have been developed for consumer durables which later served as a basis for new approaches. Leaving this category out would result in missing out on well-developed and effective indicators.

I excluded articles that focused on one industry, such as movie releases, agriculture, or focusing on successive products and multi-generations. These articles mostly use variables only applicable to their field of study, not allowing a generalization and comparison for the field of radically new high-tech innovations. After some time, articles repeated in the "related document" section, and I realized that I scanned and preselected all relevant literature.

The scanning approach resulted in 125 articles that I took for the skimming phase with a more critical and sharpened mindset. First, I started by reading the review articles[7] giving me a broad overview of concepts existing. Then I took the rest of the articles for a second reading. I skimmed through the article and the conclusion paragraph to further narrow down articles with a fit to the literature review topic. The literature review focuses on finding indicators and variables of predictive diffusion models with a specific focus on the early part of the diffusion. Therefore, I excluded articles only offering mathematical improvements of existing diffusion models or reassessed already described variables and indicators of already published models in a new manner without integrating new data sources or methods. However, I made an exception to this criterion for the article of Kim et al. (2016), later described in the findings. The article uses new theories to update a classic diffusion model, described

[7] Selected overview articles: (Chandrasekaran & Tellis, 2007; B. C. Lee et al., 2020; Mas-Machuca et al., 2014; Meade & Islam, 2006; Peres et al., 2010)

earlier in the findings, resulting in new indicators, and creating value to include it in the literature review.

After the skimming, I was left with 37 relevant articles that I used for Sections 3.2.3, 3.2.4, and 3.2.5 (see Table 4). I will describe most of the articles in detail in the following chapter. However, some articles are just referenced to showing the use of novel methodologies, especially artificial intelligence, on traditional concepts as they would otherwise exceed the scope of the literature review. Articles that have been used for the definitions in Sections 1.3.1, 1.3.2, and 3.2.2 have been selected freely based on quality and relevance defining the presented concepts.

Table 4: References for the systematic literature review of the diffusion forecasting branch

Title	Authors & Year
The Market Evolution and Sales Takeoff of Product Innovations	(Agarwal & Bayus, 2002)
A New Product Growth for Model Consumer Durables	(Bass, 1969)
Comments on “A New Product Growth for Model Consumer Durables The Bass Model”	(Bass, 2004)
Creating Growth in New Markets: A Simultaneous Model of Firm Entry and Price	(Bayus et al., 2007)
The role of prices in models of innovation diffusion	(Bottomley & Fildes, 1998)
Understanding new products’ market performance using Google Trends	(Chumnumpan & Shi, 2019)
Forecasting emerging technologies: Use of bibliometrics and patent analysis	(Daim et al., 2006)
Forecasting the diffusion of product and technology innovations: Using google trends as an example	(Duwe et al., 2018)
Forward patent citations as predictive measures for diffusion of emerging technologies	(Fallah et al., 2009)
Product sales forecasting using online reviews and historical sales data: A method combining the Bass model and sentiment analysis	(Fan et al., 2017)
Modeling seasonal effects in the Bass Forecasting Diffusion Model	(Fernández-Durán, 2014)
Will it ever fly? Modeling the takeoff of really new consumer durables	(Golder & Tellis, 1997)
The use of analogies in forecasting the annual sales of new electronics products	(Goodwin et al., 2013)
The challenges of pre-launch forecasting of adoption time series for new durable products	(Goodwin et al., 2014)
The forecasting of new product diffusion by grey model	(Guo et al., 2015)
The timeliness problem in the application of bass-type new product-growth models to durable sales forecasting	(Hyman, 1988)
Toward automatic forecasts for diffusion of innovations	(Ilonen et al., 2006)
Déjà vu: A data-centric forecasting approach through time series cross-similarity	(Kang et al., 2020)
Forecasting the diffusion of innovation: A stochastic bass model with log-normal and mean-reverting error process	(Kanniainen et al., 2011)
Can search engine data improve accuracy of demand forecasting for new products? Evidence from automotive market	(D. Kim et al., 2019)
Forecasting diffusion of innovative technology at pre-launch: A survey-based method	(T. Kim et al., 2016)
Early identification of emerging technologies: A machine learning approach using multiple patent indicators	(C. Lee et al., 2018)
Pre-launch new product demand forecasting using the Bass model: A statistical and machine learning-based approach	(H. Lee et al., 2014)
Forecasting new product diffusion using both patent citation and web search traffic	(W. S. Lee et al., 2018)
Can you see the chasm? Innovation diffusion according to rogers, bass, and moore	(Libai et al., 2009)
Timing, diffusion, and substitution of successive generations of technological innovations: The IBM mainframe case	(Mahajan & Muller, 1996)
Using stock prices to predict market events: Evidence on sales takeoff and long-term firm survival	(Markovitch & Golder, 2008)
The choice of Bass model coefficients to forecast diffusion for innovative products: An empirical investigation for new automotive technologies	(Massiani & Gohs, 2015)

Table 4 (continued)

When does the majority become a majority? Empirical analysis of the time at which main market adopters purchase the bulk of our sales	(Muller & Yogev, 2006)
Chatter matters: How twitter can open the black box of online word-of-mouth	(Rui et al., 2010)
Functional regression: A new model for predicting market penetration of new products	(Sood et al., 2009)
Quadratic-interval Bass model for new product sales diffusion	(Tseng & Hu, 2009)
Forecasting demand profiles of new products	(van Steenbergen & Mes, 2020)
The use of big data and its effects in a diffusion forecasting model for Korean reverse mortgage subscribers	(Yang et al., 2020)
A hybrid method for forecasting new product sales based on fuzzy clustering and deep learning	(Yin et al., 2020)
Improving the Bass model's predictive power through online reviews, search traffic and macroeconomic data	(Zhang, Tian, & Fan, 2020)
Product sales forecasting using macroeconomic indicators and online reviews: a method combining prospect theory and sentiment analysis	(Zhang, Tian, Fan, et al., 2020)

All articles used in this systematic literature review have been assessed by their quality and seen as sufficient or better for their purpose (see Appendix A: Quality of the systematic literature review).

Section 3.2.2 gives an overview of various historical developments in the innovation literature. Following that, in Sections 3.2.3, 3.2.4, and 3.2.5, I will describe predictive diffusion models found in the literature review classified in the following order: (i) classic models, (ii) new models, and (iii) promising new variations of existing indicators and models.

3.2.2 Approaches to predict the sales take-off of high-tech innovations

Lee et al. (2020) described that the 1990s innovation literature simultaneously analysed the demand and supply side, focusing on the product itself and its immediate environment, such as lead user theories and customer needs. In the 2000s, innovation literature shifted its focus on the company itself and the supply side by emphasizing the importance of a company's capabilities, entrepreneurial management, and the workforce. For the current decade, they are predicting a shift back to the demand side by using new data-driven methods.

To assess the approaches predicting sales take-off, I would like to use a somewhat similar classification with two categories adopted to the field of sales take-off prediction. I will start by introducing classic models relying on more traditional market data such as product price, product category, the behaviour of consumers, size of the market, or new firm entry. Afterwards, I evaluate more modern approaches using internet and social media data to measure consumer behaviour directly. Lastly, I will mention models that incorporate existing data and indicators in a novel way using machine learning techniques.

3.2.3 Classic models

As Section 1.3.2 has already shown, many different models exist forecasting the diffusion of products. The most famous model is the Bass diffusion model for consumer durables (Bass, 2004). A model out of the category cause-effect. It serves as a basis for many newer models which have been released afterwards, such as models including seasonality (Fernández-Durán, 2014), specific industries (Massiani & Gohs, 2015), successive generations (Mahajan & Muller, 1996), or mathematic improvements (Kanniainen et al., 2011; Tseng & Hu, 2009).

Bass developed as one of the first researchers a model to predict the sales of a new product (Bass, 1969, 2004). Based on *historical sales data*, the hazard model[8] predicts a curve similar to the aforementioned s-shaped curve with an additional later dip at the end of the product life. Bass defined such a curve with the help of three main coefficients (Bass, 1969):

- *coefficient of innovation*, describing external influence on the purchase of a product (Chandrasekaran & Tellis, 2007)
- *coefficient of imitation*, sometimes also referred to as word-of-mouth (Bass, 2004) or internal influence (Chandrasekaran & Tellis, 2007)
- *size of the market*

These coefficients are adjusted according to the market a new product is about to enter and its customers. By now, databases have been developed and reviewed with coefficients, allowing a more accessible application of the model on new products (Massiani & Gohs, 2015). However, the Bass diffusion model has been developed to predict well the peak of product sales (Bass, 1969). In the initial period, during the take-off, there is a lack of data to model the curve (Meade & Islam, 2006). This exists because the number of data points needs to be equal to the number of parameters (Hyman, 1988). Practically that means that if a model has three parameters, the model requires data from three subsequent years. This lack of data is a problem for radically new high-tech innovations.

To overcome this problem, Golder & Tellis (1997) started researching more about the take-off period. They began by developing a "threshold for takeoff" (Golder & Tellis, 1997). The researchers found that sales can increase steeply without meaning a take-off if the base sales[9] are low. However, the opposite is the case if the base sales are high. Therefore the "threshold for takeoff" is dependent on the base sales volume. Concluding this, a take-off happened if product sales crossed the threshold.

Next, Golder & Tellis (1997) used a hazard model with three independent variables and six control variables to model the take-off based on a cause-effect approach:

- *Product price*
- *Year of introduction*
- *Market penetration*
- Control variables (Except for unit sales, all have been proven as not significant)
    - Product-specific variables
        - Unit sales
        - Network externalities
        - Product category
    - Economic variables
        - Gross National Product
        - Number of households
        - Consumer sentiment measured by economic characteristics

[8] Definition Hazard Model: A statistical method to calculate the probability that an event happens during a predefined time (Heckman & Singer, 1984)

[9] Definition Base Sales: The number of products a company would have sold without any advertising or marketing.

The developed model can predict a sales take-off at the time of introduction with a mean error of roughly two years or one year ahead with a mean error of almost 1,2 years (Golder & Tellis, 1997). As particularly important for the take-off have been proven the variables price and market penetration.

Similarly, Agarwal & Bayus (2002) also use the variable *price* complemented by the variable *new firm entry*. As control variables, they use the year of commercialization, product type, and World War II. Their studies conclude that *new firm entry* and *price decline* specify the take-off. They do not use a parametrized hazard model like Golder & Tellis regarding the predictive feature of their cause-effect model but suggest using the "relationship between sales take-off time and *new firm entry*" (Agarwal & Bayus, 2002) out of practical reasons. They refrain from using the *product price* as a predicting variable due to weak results in later studies (Bayus et al., 2007; Bottomley & Fildes, 1998). However, they see the *product price* as an endogenous variable, unlike Golder & Tellis and their earlier publications (Bayus et al., 2007). Therefore, they classify the *product price*, influenced by *firm entry*, as an indirect relationship with sales take-off. The *product price* reduces because more supply is available in the market. Additionally, they describe an influence of the *firm entry* and *price* by the exogenous variables *patent stock*, *large firms*, and *R&D costs* (Bayus et al., 2007). Nevertheless, a concrete predictive model has not been developed.

Another method to solve the problem of missing data in the early period of diffusion is to use the analogy approach (Goodwin et al., 2013; Meade & Islam, 2006). Yet, the method has been proven as not very trivial and relatively ineffective (Goodwin et al., 2013). Therefore, Goodwin (2014) describes a need for different forecasting models. One idea is to use judgemental models. However, these models introduce bias into the forecasting process. Therefore, a judgemental feature should mainly be used for sub-tasks of the forecasting, input factors, or interpretation, such as management decisions based on a cause-effect method (Goodwin et al., 2014).

Besides using judgemental features, a promising approach is using internet and social media data. Forecasting models integrating this data will be described in the next section.

3.2.4 New models

To classify the new models, I sorted them into two main categories: the supply side and the demand side. While the first models will use bibliometrics, patent data, and stock prices to measure a technology's potential (supply of new products), the latter will try to measure word-of-mouth and marketing efforts by using social media data and search trends (demand of new products). The similarity both categories have is that the internet facilitated the data collection creating a new class of diffusion models, the so-called new models.

Supply side

Daim et al. (2006) were one of the first that developed a cause-effect diffusion model incorporating *patent analysis data* and *bibliometrics*. They separated the two methods and developed two applications integrating *patent data* and one application integrating *bibliometrics*. For the first two applications, they argue that *patent data* is an indicator of technological trends and technology battles and can be, therefore, used as an early indicator for technology diffusion. The validity of the indicator is explained by the lengthy and costly process to file a patent, meaning that one must be confident that a particular technology's profits will exceed the initial investment. For their growth curve, they assess the *quantity of patents* filed, as well as the *quality of patents*. The quantity curve resembles the s-shaped curve it can directly be integrated into a prediction model. Quality measurements are used in a judgemental method complementing the cause-effect approach.

On the other hand, they use *bibliometric data* for a different application scenario. *Bibliometric data* includes authors, affiliations, citations, clusters, and many more (Daim et al., 2006). The authors suggest that *bibliometric data* can reveal hidden patterns in past data and potentially forecast future developments in the scientific area. As indices, they use different sources per life cycle stage. The Initial basic research stage is represented by a database of scientific citations, the development stage by US patents, and the application stage by newspaper abstracts to just mention three out of five stages. Collected data will be fit into an s-shaped curve to be then integrated into a predictive model.

It is not entirely clear why different forecasting approaches have been applied to different technologies instead of using them on the same kind of technology, allowing the researchers and reader to compare the results. Hence, one may suggest that technologies have been selected by the researchers giving satisfactory results with the forecasting approach.

Other authors use a different kind of patent analysis to improve their predictive model. For example, Fallah et al. (2009) are using *forward citations of patents* to predict the emerging of new technologies. Their results describe that cumulative forward citations of patents are not following an s-shaped curve. Instead, forward citations are growing linearly until reaching a plateau. This finding is, however, classified as work in progress. More research is needed to understand the relationship and to develop a cause-effect forecasting model. Until now, the research has not been refined by the authors.

Lee et al. (2018) used a neural network on patent data to calculate a "technology's emergingness." This key indicator is based upon various sub-indicator in the categories:

- *Novelty of the patent*
- *Science-intensity*
- *Growth speed*
- *Scope and coverage*
- *Development effort and capabilities*

The study describes a complex approach deploying an automatic AI system to forecast technology emerging right from a patent's release date. However, the systematic method cannot forecast the time a technology needs to diffuse, relying only on patent indicators. Nevertheless, it should be emphasized that the framework does not require any judgemental indicators, decreasing the bias of the analysis.

Markovitch & Golder (2008), an author already known from the section of classic models, researched the indicational feature of stock prices before sales take-off. In detail, they used the indicator *abnormal stock returns* of a company to measure shocks in stock prices in a cause-effect manner. These shocks can represent, for example, company announcements such as performance increases or competitor's entry or exit. Their study shows that positive shocks on a product category's stock market are common a year before take-off. Therefore, stock prices can be used to reflect news items of a technological area quantitatively. Additionally, they found out that the number of incumbent firms increases in the year of sales take-off — a somewhat similar finding to Agarwal and Bayus' *new firm entry* indicator.

Demand side

Various cause-effect models use google search trend data, which is freely available on the internet, to improve demand forecasting (Chumnumpan & Shi, 2019; Duwe et al., 2018; D. Kim et al., 2019). For example, Chumnumpan & Shi (2019) have successfully used the *search data* of iPhones and iPads to nowcast[10] their current sales numbers. They explain that the *search trend data* can be an excellent indicator to estimate current sales data, which is often only available in a retrospective but not in real-time. In addition, this approach could help to calculate sales data that might be kept confidential by a competing company.

Alternatively, Duwe et al. (2018) tried to use the same data to forecast the diffusion of products in the early stage. This application of the *search trend data* was relatively unsuccessful because data would only cover "mainstream interest and expectation" (Duwe et al., 2018, p. 6). However, they suggest comparing *sales data* and *search trend data* as an indicator to forecast a potential increase in sales in the market. Their less successful results could also be explained by the nature of the selected search terms. Apple products, like the ones used by Chumnumpan & Shi, are usually popular on social media and clearly defined search terms result in more reliable *search trend data* than the search terms used by Duwe et al., like Blu-ray, mobile instant messaging, and smartphone cameras.

Kim et al. (2019) used *search trend data* to model the coefficients of the Bass diffusion model (see Section 3.2.3) instead of using sales data as in the classic model. They argue that search trend data includes internal and external effects of the purchase decision, such as information available, exposure to advertisements, and word-of-mouth. The main findings of the research are the proposed formulas to calculate the coefficients based on a cause-effect relationship. After a series of comparisons with existing diffusion models, they conclude that the developed relationships can be used in about 84% of the cases to successfully predict the sales of new products over the product lifecycle. However, it was not disclosed how well the models predict the point of sales take-off.

Instead of using simple search data, Fan et al. (2017) developed a variation of the traditional Bass model integrating online reviews analyzed by sentiment analysis[11]. They extract the *sentiment index* via an AI algorithm from online reviews and include it into the *coefficient of imitation* of the Bass

[10] Definition Nowcasting: "The prediction of the present, the very near future and the very recent past." (Banbura et al., 2010, p. 4)

[11] Definition Sentiment Analysis: "A [natural language processing] technique to detect favorable and unfavorable opinions toward specific subjects (such as organizations and their products) within large numbers of documents […]." (Nasukawa & Yi, 2003, p. 1)

diffusion model. Therefore, they define that online reviews have a relationship to word-of-mouth and the internal factors during a purchase decision (see Section 3.2.3).

Another approach to measure word-of-mouth describes the research by Rui et al. (2010). They used sentiment analysis on Tweets to predict the revenue of movie box sales. However, I will not discuss their findings in detail as forecasting the success of movie productions is a research area on its own.

A research project that should also not go unmentioned is the work by Zhang, Tian, & Fan (2020) and Zhang, Tian, Fan, et al. (2020). They successfully combined modern indicators into the Bass diffusion model coefficients, resulting in the following relationship:

- Online review sentiment for the *coefficient of imitation* based on AI
- Search trend data for the *coefficient of innovation* based on a cause-effect relationship
- Macroeconomic data to measure the *size of the market* based on a cause-effect relationship

Their research showed that incorporating macroeconomic data had the most considerable improvement on the predictive power of the classic model (Zhang, Tian, & Fan, 2020). However, it remains unclear how well the model predicts the sales take-off, which limited the traditional Bass diffusion model. This challenge will be further discussed in the next section focusing on existing indicators that have been used in novel methods to develop models predicting the sales take-off.

3.2.5 Promising new variations of existing indicators and models

Kim et al. (2016) reassessed the Bass diffusion model, focusing on predicting the sales take-off. First, they split the diffusion curve into two parts covering (i) the initial take-off until the saddle as the early market (compare Section 1.3.2) and (ii) the large-scale diffusion after the saddle as the mass market. Then they altered the *coefficient of innovation* for the mass market to capture mass media influence and early adopter influence on main market adopters. The concept that early adopters communicate with the mass market adopter is also called cross-market communication, a highly debated concept in the research area (Libai et al., 2009; Muller & Yogev, 2006).

Following this line of argumentation Muller & Yogev (2006) came up with a rule of thumb. On average, a mass market is reached after 16% of the market adopted a product. However, the application of the rule of thumb, stemming from a generalization, is limited to predict large-scale diffusion of specific products.

Several models integrate machine learning principles to analyze already existing indicators in a new way (Guo et al., 2015; Ilonen et al., 2006; Kang et al., 2020; H. Lee et al., 2014; W. S. Lee et al., 2018; Sood et al., 2009; van Steenbergen & Mes, 2020; Yang et al., 2020; Yin et al., 2020). However, these models will not be part of the literature review as they do not introduce entirely new variables.

3.2.6 Discussion & Conclusions

In this section, the findings of the systematic literature review will be discussed and a conclusion drawn.

Indicators found in the literature research

Categories could be found after which models have been clustered accordingly: (i) classic models, (ii) new models, and (iii) promising new variations of existing indicators and models.

Besides this, distinctive indicators predicting a sales take-off or the emerging of a product have been described and discussed in the findings. The main indicators found are shown in Table 5, in addition to the main output and input factor of (historical) sales data.

Most researchers use a variety of indicators to predict sales. Nevertheless, only a few researchers developed models integrating indicators from various categories. Moreover, it can be seen that some indicators can only be calculated by the company in focus, such as *market penetration* based on the sales data, which might not be publicly available. Still, there might be a chance to calculate such data by analyzing search trends (Chumnumpan & Shi, 2019).

However, not all indicators with the source company in focus are confidential. For example, the indicators *new firm entry* and *year of introduction* can also be found on company websites or retailers and are therefore publicly available. Moreover, data from Google Trends, patent databases, and stock markets are available to everybody for no cost. If a fee is paid, also scientific libraries offer their services regarding *bibliometric data* to the public. Additionally, all indicators except the variable *quality of patents* are determined without any judgemental opinion and are purely quantitative. This quantitative focus helps to predict and calculate the sales take-off without any bias.

It should not be forgotten that sales data is not available before the large-scale diffusion. Therefore, the relevance of models using historical sales data (mostly classic models and models based on the Bass diffusion model) is low for predicting the sales take-off of radically new high-tech innovations due to the missing analogies from other comparable product categories. In these cases, other variables giving an earlier indication are necessary.

Table 5: Main indicators and their data source and article mentioned

Category	Indicator	Data Source	Article
Bass diffusion model factors	Coefficient of innovation	Coefficient database of product categories	(Bass, 1969)
		Sentiment index of online reviews	(Fan et al., 2017; Zhang, Tian, & Fan, 2020; Zhang, Tian, Fan, et al., 2020)
	Coefficient of imitation	Coefficient database of product categories	(Bass, 1969)
		Search trend data	(Zhang, Tian, & Fan, 2020; Zhang, Tian, Fan, et al., 2020)
	Size of the market	Company in focus	(Bass, 1969)
		Macroeconomic data	(Zhang, Tian, & Fan, 2020; Zhang, Tian, Fan, et al., 2020)

Table 5 (continued)

Market factors	Product price	Retailer	(Agarwal & Bayus, 2002; Bayus et al., 2007; Golder & Tellis, 1997)
	Year of introduction	Company in focus	(Golder & Tellis, 1997)
	Market penetration	Company in focus	
	New firm entry	Competitor company	(Agarwal & Bayus, 2002; Bayus et al., 2007)
	New incumbent firm entry	Competitor company	(Markovitch & Golder, 2008)
Technology factors	Quality of patents	Expert opinion	(Daim et al., 2006)
	Quantity of patents	Patent database	
	Forward citations of patents		(Fallah et al., 2009; C. Lee et al., 2018)
	Novelty of the patent		(C. Lee et al., 2018)
	Science-intensity		
	Growth speed		
	Scope and coverage		
	Development effort and capabilities		
	Bibliometric data	Scientific, patent, & newspaper libraries	(Daim et al., 2006)
Stock market factors	Abnormal stock returns	Stock market	(Markovitch & Golder, 2008)

Lastly, the question arises of how these indicators predict diffusion. In the reviewed articles, two main types of prediction methods could have been found. On the one hand, the Bass diffusion model and all related models (Bass, 1969; Fan et al., 2017; Zhang, Tian, & Fan, 2020; Zhang, Tian, Fan, et al., 2020) are using a curve-fitting approach. These models use growth curves resembling an s-shape to forecast the diffusion of an innovation. On the other hand, Agarwal & Bayus (2002), Bayus et al. (2007), Markovitch & Golder (2008), and Golder & Tellis (1997) use the Cox regression.

Takeaways from the diffusion forecasting branch

It was shown that data for the classic indicators are scarce before the sales take-off, and the new models do not consistently deliver an approach forecasting reliably the time until the take-off of new innovations. Furthermore, most research focuses on predicting the peak point of diffusion, a later point in the diffusion curve. Therefore, more research is needed to identify and organize multiple potential indicators observing and predicting the upcoming diffusion of new innovations.

3.3 Scoping literature review: Macroenvironment branch

3.3.1 Introduction to the macroenvironment branch

Kotler (2003) identifies the importance of scanning the environment around an innovating firm. First, he describes the concept of macroenvironmental forces. These forces are characterized by trends and needs customers will develop in the future and are from a firm's perspective "noncontrollable" (Kotler, 2003, p. 161). Therefore, a firm must predict and observe these forces and react quickly to them. Alternatively, Else, other firms will take over shortly in case new trends are not fulfilled. Macroenvironmental forces are driven by six sub-classes, which will be defined below: demographic, economic, natural, technological, political-legal, and socio-cultural environment (Kotler, 2003).

Demographic environment

The first sub-environment describes the future customers of a technology. This description includes age or generation, ethnicity, educational background, household structure, and geographics.

Economic environment

The economic environment is mainly influenced by a customer's prosperity and income distribution and its financial structure in the forms of savings, debts, and accessibility to credits. However, the economic environment also includes actors upstream of the value chain, such as suppliers. Their economic status also influences the company in focus. For example, if a supplier might not deliver material or components due to financial constraints, the company in focus cannot manufacture and subsequently sell its products.

Natural environment

This type of sub-environment concerns all actions and movements regarding a more sustainable future. Foremost, unrestricted access to raw materials plays a significant role, increased energy costs, sustainability efforts and a greener political agenda.

Technological environment

Time-to-market of competitors but also the fast pace of technological change are critical determinants of the technological environment. Moreover, growing numbers of innovation opportunities, changing R&D budgets, and increasing numbers of technology regulating policies influence the technological environment.

Political-legal environment

Although legal forces have already been mentioned in earlier sub-environments, political decisions about business legislation and NGOs increasingly interfere with technological innovations.

Socio-cultural environment

The last sub-environment refers to more loose concepts, such as the self-view and the view on external artefacts such as others, organizations, and the society as a whole. These views are influenced by changing cultural values and subcultures.

Takeaways from the macroenvironment branch

The macroenvironment branch, represented by findings from Kotler, does not serve as a direct source for indicators of diffusion prediction. Nevertheless, the macroenvironment branch classifies the macroenvironment around an innovating firm into six sub-classes using a company perspective. This classification can serve as an inspiration for more indicators and a foundation for a review if the later selected indicators cover the holistic environment around a new innovation.

3.3.2 Indicators from the macroenvironment branch

Five indicators could have been derived from the macroenvironment branch based on the macroenvironmental forces a company faces. Indicators have been derived from a perspective of a company in a competitive environment. An overview of the derived indicators and their data source is shown at the end of the section in Table 6. Most of the indicators are qualitative, with an exception to the indicator of the customer's prosperity.

Availability of materials and suppliers

The *availability of materials and suppliers* plays a crucial role to produce a product. Unavailability of material can unnecessarily postpone production, although the market is ready for innovation. This problem might also occur in services. Nowadays, many online services rely on machine learning platforms. If these platforms or materials are not available in the scale needed, diffusion is hampered. The indicator is dichotomous, showing if materials are available in a sufficient amount, and in its nature a technology indicator. However, the supply of materials and services is also a market from the perspective of an innovating firm. Hence, the indicator has been categorized as a market indicator.

Education

The indicator *Education* stems from the demographic macroenvironment. The educational background of customers and employees plays an essential role during the adoption of a new innovation. In this case, however, the sole education of employees working for an innovating firm are considered. High-tech innovations require trained and well-educated personnel in various scientific areas to develop new technologies. A lack of education in critical scientific fields might lead to a slow development phase or the non-existence of a development phase. Diffusion of a new technology might not start or start substantially later if knowledgeable personnel is lacking.

Identified as a megatrend

A very much forward-looking indicator is the identification as a megatrend[12]. Many market research firms or experts give early indications of possible future trends (Kotler, 2003). However, the selection process for technologies is not unified, and each market research firm uses different measures or methods to select the megatrends. The selection process results are available in reports for free, a

[12] Definition Megatrend: Megatrends are "large social, economic, political and technological changes [that]are slow to form, and once in place, they influence us for some time – between seven and ten years, or longer." (Naisbitt & Aburdene, 1990)

one-time fee or a yearly subscription depending on the business model of the market research firm. One of the megatrend indicators is the hype cycle report by Gartner (see Section 3.5).

Recognizing a technology as a megatrend could work as an early dichotomous indicator to predict the start of diffusion at a later point in time. Many times, once a technology has been recognized as a megatrend, exploration and development by research institutes and companies is still necessary to produce a product that is ready for the market. Due to the complexity of the construct measured and its various external influences, the indicator is classified as contextual.

Laws and Regulation

The contextual indicator *Laws and Regulation* measures qualitatively if current legislation supports a diffusion of a product. Laws and regulations play a crucial role during the innovation and diffusion phase (Kotler, 2003). For example, electric scooters need to receive homologation before entering the customer market. Similarly, laws for recreational drones had to be drawn up to give customers clarity and safeguard high-risk air space. Missing regulation hampers diffusion because customers face uncertainty about the application of a technology (in the case of drones), or they do not have access to buying a product if it is a highly regulated market segment (in the case of electric scooters).

The last example can lead to a segregated diffusion because each country can develop their laws. In the case of electric scooters, some countries like the Netherlands still block the diffusion of electric scooters. At the same time, the majority of Europe provides a legal basis for the homologation and use of electric scooters.

Purchasing power

Purchasing power is defined as the "amount of money that a person or group has available to spend" (Merriam-Webster, 2021b). Therefore, a customer's prosperity can be measured by its purchasing power. If a customer earns relatively a lot compared to a country's cost of living, the customer can spend more money on products and services. A customer would be more willing to spend money on a new product, especially if the new product is a consumer durable or not a necessity for the minimum standard of living.

The indicator's value can be retrieved at a country's statistical institute for the whole country. If data about selected customer groups is required, market surveys can help to receive more detailed insights. *Purchasing power* is a quantitative indicator and focuses on a market's readiness to purchase a new product or service.

Supportive niche communities

Socio-cultural environment forces are forming sub-classes in our society (Kotler, 2003). Derived from this niche, small communities can support the development and diffusion of a new innovation. If niche communities are closely connected and members communicate with each other, they can support the innovating firm during the pre-diffusion phase. While companies try to develop a product for the mass market, lead users in niche communities can assist companies in open innovation approaches.

Nowadays, innovators and early adopters can easily communicate via online forums. Companies can leverage these communities to define customer requirements quicker and reduce uncertainty.

Table 6: Indicators derived from the macroenvironment branch

Indicator	Data Source	Focus of Indicator	Type of Indicator
Availability of materials and suppliers	Expert opinion	Technology	Dichotomous
Education	Expert opinion	Contextual	Qualitative
Identified as a megatrend	Market research firms, expert opinion	Contextual	Dichotomous
Laws and Regulation	Expert opinion	Contextual	Qualitative
Purchasing power	A country's statistical institute	Market	Quantitative
Supportive niche communities	Expert opinion	Contextual	Qualitative

3.4 Scoping literature review: Dominant Design branch

3.4.1 Introduction to the dominant design branch

The dominant design branch describes the observed behaviour until an innovation is selected as the common standard. Whereas the dominant design describes a milestone and transition point in an industry (Suárez & Utterback, 1995). It incorporates the needs of various customer groups while not necessarily fulfilling the requirements of a particular customer group fully.

In history, two approaches have been identified: the de facto and the de jure approach. While in the first approach, a standard and dominant design are derived by competition, in the second approach, a dominant design is decided upon via consensus (David & Greenstein, 1990).

Abernathy and Utterback (1978) further described the competition-based standardization approach by defining three stages: fluid, transitional, and specific pattern. For us relevant is only the change from the fluid pattern to the transitional pattern. During this change, process innovations outnumber product innovations in a new technical regime.

The authors describe this increase in process innovations as preparation for mass production, which precedes closely large-scale diffusion. Companies apply economies of scale because they must increase their profitability after experimenting with many incremental innovations. Moreover, the goals of the innovation and the target market become well defined due to technological advances and customer research. According to the authors, these well-defined requirements allow bigger investments and long-term decisions, moving closer to the mass market.

Following the work of Abernathy and Utterback, Anderson and Tushman (1990) developed the evolutionary model of technological change. The evolutionary model describes how a breakthrough innovation starts an era of ferment, leading to a dominant design which is subsequently improved in the era of incremental change. Then the last era ends abruptly due to a new breakthrough innovation discontinuing the earlier technology, closing the technology cycle.

Relating Anderson and Tushman's research to this master thesis, the focus lies on the era of ferment until a dominant design emerges from the competition. The era of ferment creates a path for standard selection via "two distinct selection processes: competition between technical regimes and competition within the new technical regime" (Anderson & Tushman, 1990, p. 611). In contrast, Suárez and Utterback described the selection of a dominant design as a "fortunate combination of technological, economic and organizational factors" (Suárez & Utterback, 1995, p. 417). This definition translates to the belief in a more random and free selection of a dominant design. Nevertheless, the selection and diffusion is based upon "underlying dynamics of the industry life cycle" (Suárez et al., 2015, p. 443)

Tushman and Rosenkopf (1992) conclude that the greater the technical uncertainty is, the greater is the interference of non-technical forces onto the development of a product. This relation is fundamental as new innovations are generally fuzzy regarding their technical specifications, needs and use case. Non-technical forces or environments influencing a technology's path will be further discussed in the macroenvironment branch literature review in Section 3.3.

As part of the dominant design theory, Suárez et al. (2015) established the concept of the dominant category. A dominant category is the product category in which a dominant design will be positioned. They not only see the category as a technical classification but also as a socio-cognitive definition in which other actors besides the manufacturer can create a product category.

The authors describe the graph showing the number of product categories over time by the typical bell curve shape (Suárez et al., 2015). This means that the number of categories increases after invention because the technology is uncertain. Then it reaches its peak point once uncertainty decreases and a dominant category is selected. After the given time point, the number of categories decreases and the innovation diffusion beings.

Inside the dominant design branch, the field of standards battles has emerged. The field of standards battles aims at analysing the winner of a de facto battle among various competing standards. Van de Kaa et al. (2011) provides a holistic framework of 29 factors analysing the potential winner of a standards battle, which has been applied on various cases (e.g. van de Kaa et al., 2014, 2017, 2020). There the standard is seen as a format or individual product of a technology as such. This viewpoint of standards is more detailed than the technology or innovation in focus in this master thesis.

For the theory of the model, the authors draw on scholars from four literature streams inside the dominant design branch. They conclude that the evolutionary economists (e.g. Utterback, Abernathy, Tushman and Anderson), which have been described above, "focus on the speed and likelihood" (van de Kaa et al., 2011, p. 1400) of standard dominance. This literature stream correlates highly with the scope of this research. The speed of format dominance translates in the context of the master thesis to the timeliness of the diffusion, although not necessarily to the start of diffusion. The other three literature streams are less relevant to the research due to their focus on individual market mechanisms, characteristics of individual firms and characteristics of the individual standard in focus.

As a result, the diffusion of an innovation happens on a higher level and performs less on an individual project level.

To involve all possible indicators measuring the speed and likelihood of format dominance, the indicators of the Van de Kaa framework in the category market characteristics will be included: Bandwagon effect, network externalities, number of options available, uncertainty in the market, rate of change, and switching costs (van de Kaa et al., 2011). On the other hand, other categories will be excluded as they claim only to have an “impact on the format dominance” but not its speed of format dominance (van de Kaa et al., 2011, p. 1403).[13]

Takeaways from the dominant design branch

Concluding the findings of the dominant design branch, researchers emphasize the importance of the shift from the fluid to the transitional phase. This importance confirms the research focus of this master thesis, searching and deriving indicators for the upcoming diffusion of an innovation. However, prediction of the start of diffusion is not a common theme of the dominant design branch. Dominant design research mainly describes the phases and analyses why a specific technology format has emerged as a standard. The timing of the diffusion is a secondary research focus of the branch.

3.4.2 Indicators from the dominant design branch

In fact, the dominant design branch, the field of standards battles, directly offers a rich pool of indicators. However, as explained before, not all indicators are relevant to anticipate the start of large-scale diffusion. Nevertheless, the theories of the dominant design branch still apply to the pre-diffusion phase. Hence, 17 indicators could have been derived or found in the dominant design literature. An overview of the indicators is given at the end of the section (see Table 7).

A problem to be solved exists

The indicator *A problem to be solved exists* emerged from mechanisms that have been described in the dominant design literature. The idea behind the indicator is that customers see a problem in their life or job that can be solved by a product or service for an economical price point. The value derived from solving the problem needs to be higher than the cost of the product or service. This dichotomous market indicator requires customer focus groups and expert opinions to come to a reliable value. Usually, such an assessment is possible during the development of a product.

Associations, coalitions, or groups formed

Companies sometimes form coalitions to agree on terms of standards or norms (Schilling, 2013). The formation of these groups signals joint efforts to achieve compatibility. These could translate into a

[13] A few indicators found in these categories will still be included in the list of observing indicators (see the following section). In these cases, the indicators have been proven or described to measure a construct related to the timeliness of innovation diffusion.

mutual interest of competitors to enter the market soon. Hence, such a formation of coalitions might signal the start of diffusion.

However, not all innovations require the formation of associations or coalitions. While sometimes compatibility is not needed or purposively not required, other standards emerge or are defined by government institutions. The indicators are highly contextual, depending on the type of innovation and of a dichotomous type.

Automatization of production increases

With the ongoing development of a product, the automatization of production systems tends to increase (Abernathy & Utterback, 1978). This increasing automatization is due to the increase of process innovation after a major product innovation. Production plants try to get ready for large-scale production before the company enters the mass market. The technology indicator is quantitative, measuring the percentage of automatization over the overall production. Unfortunately, information about production plants is usually scarce. However, from time to time, companies publish information in company blogs. Moreover, experts might help to identify the correct degree of automatization.

Bandwagon effect

The *Bandwagon effect* describes the behaviour that customers tend to copy customers' practices with similar problems who already have found a solution. This behaviour speeds up the diffusion of a technology affecting an earlier start of large-scale diffusion. The qualitative indicator found in the literature by Van de Kaa assesses customers' behaviour in the market.

Certain customer requirements

At the beginning of developing a radically new product, customer requirements are uncertain (Suárez et al., 2015). Companies then use the pre-diffusion phase to test out various smaller innovation projects find the right product-customer fit. The more time advances, customer requirements usually get the more confident in predicting the start of large-scale diffusion. The indicator is qualitative due to the complex and diverse underlying construct of customer requirements. Experts might help to summarize customer requirements from focus groups into a market indicator. The here described indicator matches the Van de Kaa factor uncertainty in the market.

Certain product specifications

Similarly to the customer requirements, product specifications are usually uncertain but get more focused over time (Suárez et al., 2015). Product specifications are also up for testing during the pre-diffusion phase and get more specific towards the end of the phase. Compared to the customer requirements varying product specifications are easier to measure as they rely on a more practical construct. The technology indicator is measured qualitatively by experts.

Dominant category selected

The concept dominant category summarizes the product specifications construct well into a more approachable concept. The concept, established by Suárez et al. (2015), will also be measured by an expert but is of a dichotomous type. Once a dominant category is selected, customer requirements and product specifications are less volatile, and a dominant category emerged from the interplay of the supply and demand side. Then, the diffusion of an innovation is more likely than before.

Dominant design selected

The market indicator succeeding the dominant category is the dominant design. After most innovations stem from the same product category, a dominant design materializes (Suárez et al., 2015). This already widely discussed concept could predict the start of large-scale diffusion. The market indicator is also dichotomous and can only be measured by an industry expert.

Frequency of product changes decreases

The indicator *Frequency of product changes decreases* is a quantified version of the indicator dominant category selected and certain product specifications (cf. Abernathy & Utterback, 1978; Suárez et al., 2015). The indicator describes well the underlying concept. The technology indicator measures how often radical product changes are happening. Once the frequency slows down, a dominant category is selected, and product specifications are more specific than before. The technology indicator is quantitative and relies as the other two indicators on an expert opinion. The expert has to define what a radical product change is in the product category, presenting an opportunity for bias. The here described indicator matches the Van de Kaa factor rate of change.

Network externalities

Network externalities are described as "the effect that the utility an individual user derives from consumption of a good increases with the number of other agents consuming the good" (van de Kaa et al., 2011, p. 1406). The qualitative indicator has been found in the literature by Van de Kaa, who concludes that increased network externalities increase the likelihood of standard dominance. An expert is needed to assess the network externalities of the technology.

New firm entry

Similarly to Agarwal & Bayus, the dominant design branch suggests that *New firm entry* might indicate the start of large-scale diffusion. Data for the quantitative market indicator can be retrieved at online and offline retailers. The here described indicator matches the Van de Kaa factor number of options available.

Number of product categories decreases

As the indicator dominant category selected suggests, the number of product categories decreases over time as the customer requirements get more certain. The market indicator *Number of product categories decreases* precedes the selection of the dominant category and might, therefore, indicate the large-scale diffusion earlier. However, the classification of products into categories is up for bias by an expert and might not be accessible due to the existence of limited products and producers.

Product performance increases

Product performance constantly increases during the era of ferment even though the radical change did happen through technological discontinuity (Anderson & Tushman, 1990; Rosenkopf & Tushman, 1992). This theory is also confirmed by Abernathy & Utterback (1978), showing a higher rate of innovation during the fluid and transitional pattern. The diffusion of innovation usually starts during the shift from the fluid transitional phase. Hence, increasing product performance could suggest the start of diffusion. The quantitative indicator is purely based upon the technology, leading to an objective assessment.

Production capacity increases

As mentioned before, increasing automatization in production might suggest the start of diffusion. Even the capacity increase in the production plant can suggest the start of large-scale production and diffusion on a more superficial level. Such information is not often shared, but an increase in operational job vacancies might imply the same. Therefore, the quantitative technology indicator relies on the information published by the company in focus. However, an industry expert with connections to companies may have information or news to share.

Quantity of patents

As the literature review of the diffusion forecasting branch (see Section 3.2) has already shown, the *Quantity of patents* is a widely used indicator in forecasting models. However, the dominant design branch also implies that the number of patents might be a promising indicator to anticipate the start of large-scale diffusion. The indicator can reveal that companies develop a new innovation and have high expectations for its market launch. A patent application is a lengthy and costly process (Schilling, 2013). As already mentioned in the section for the diffusion forecasting branch, the indicator is quantitative and technology-focused. Data can be retrieved from patent databases.

Standards exist

While the dominant design indicator looks out for similar product models, the *Standards exist* indicator shows if a technological standard has been developed or agreed on. The agreed standard might be the outcome of an association or coalition promoting compatibility. A technology expert best evaluates the dichotomous technology indicator.

Switching costs

Usually, customers face costs when switching from a predecessor's platform or product to new technology. If the *Switching costs* are high, the diffusion is hampered because customers will stick longer with a predecessor's technology until the value derived from the new technology is higher than the switching costs. The quantitative indicator has been found in Van de Kaa's literature and depends on the technology in focus. An expert opinion is needed to determine all costs emerging from a technology change.

Table 7: Indicators derived from the dominant design branch

Indicator	Data Source	Focus of Indicator	Type of Indicator
A problem to be solved exists	Customer focus groups, expert opinion	Market	Dichotomous
Associations, coalitions, or groups formed	Expert opinion	Contextual	Dichotomous
Automatization of production increases	Company news, expert opinion	Technology	Quantitative

Table 7 (continued)

Bandwagon effect	Expert opinion	Market	Qualitative
Certain customer requirements	Expert opinion, customer focus groups	Market	Qualitative
Certain product specifications	Expert opinion	Technology	Qualitative
Dominant category selected	Expert opinion	Market	Dichotomous
Dominant design selected	Expert opinion	Market	Dichotomous
Frequency of product changes decreases	Expert opinion	Technology	Quantitative
Network externalities	Expert opinion	Technology	Qualitative
New firm entry	Retailer	Market	Quantitative
Number of product categories decreases	Expert opinion, retailer	Market	Quantitative
Product performance increases	Product data sheet, product reviews	Technology	Quantitative
Production capacity increases	Company news, expert opinion	Technology	Quantitative
Quantity of patents	Patent database	Technology	Quantitative
Standards exist	Expert opinion	Technology	Dichotomous
Switching costs	Expert opinion	Technology	Quantitative

3.5 Scoping literature review: Crossing the Chasm branch

3.5.1 Introduction to the crossing the chasm branch

"Crossing the Chasm" by Moore is another theory explaining the transition from the pre-diffusion phase to the stabilisation phase. Moore describes his findings of making the jump from the early adopters[14] in the pre-diffusion phase to the early majority in the stabilisation phase.

Building upon the technology adoption life cycle by Rogers Moore (2014) developed the theory of crossing the chasm. A chasm opens between the early adopters and the early majority in the well-known bell-shaped technology adoption life cycle (see Figure 10). This chasm primarily results from the different needs customers have in the two product life cycle stages. For companies, the transition between the two stages is far from easy. While earlier customers bet on new technology because of its novelty and disruption, later customers look for a significant productivity improvement over the old technology.

[14] Moore uses different names for the customer groups emphasizing their character. For clarity reasons, I will use the names established by Rogers.

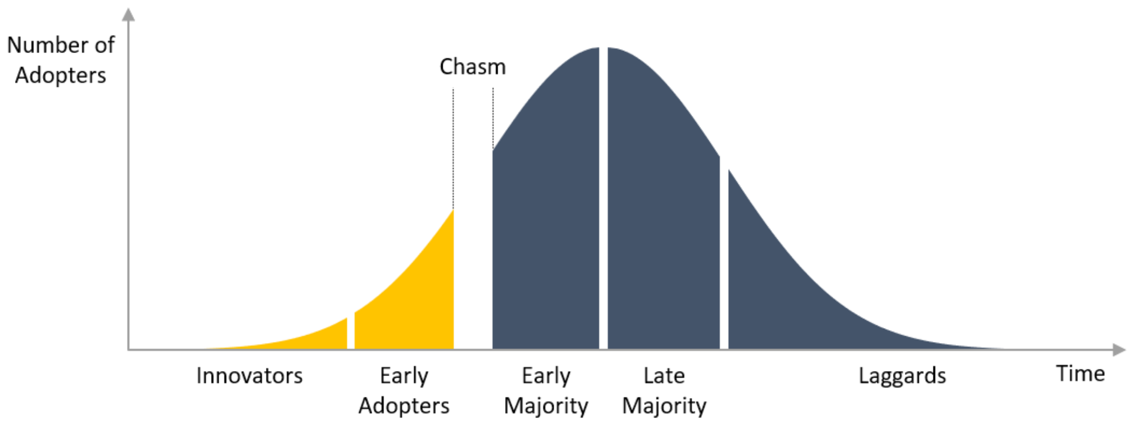


Figure 10: Technology Adoption Life Cycle with Chasm (adapted from Moore, 2014)

Moore's preferred introduction strategy is a niche strategy to overcome the chasm. He uses an analogy from the war, the so-called beachhead. By focusing its resources on a niche product in a beachhead segment, a company should get access to the mass market at a later point in time (Moore, 2014). The company can move on from the beachhead segment as soon as it has secured the niche. For this reason, the beachhead segment should be:

- Big enough to make an impact in the mass market
- Small enough to reach segment leadership easily
- Matching a company's core competencies and capabilities

However, entry strategies are not the scope of the master thesis, and most of Moore's research is not directly relevant to the topic. Nevertheless, Moore visualized the transition between the customer groups in a matrix and described activities happening at the first four stages of the Technology Adoption Life Cycle (see Figure 11).

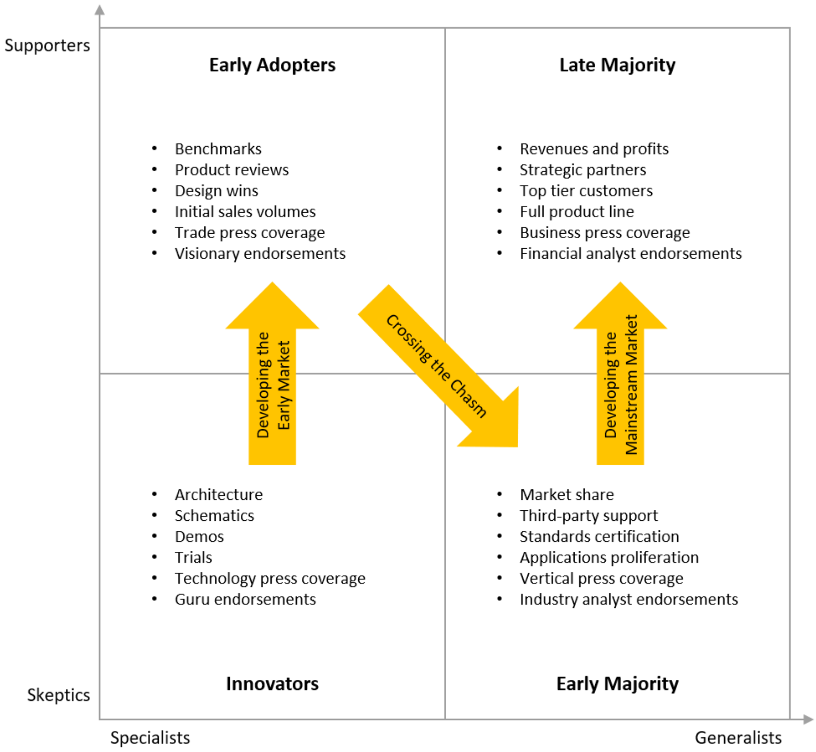


Figure 11: Characteristics of the transition between customer groups (adapted from Moore, 2014)

For us, in interest are quadrants two and three, Early Adopters and Innovators, respectively. Most activities in the Innovators quadrant, the first stage in the life cycle, are hard to measure except the technology press coverage. In the second stage of the life cycle, before large-scale diffusion, trade press coverage, initial sales volumes, product reviews, and design wins are rather measurable constructs. However, one should be careful while interpreting the media coverage (compare Figure 13).

Gartner's Hype Cycle

Gartner, a market research firm, developed a visual pattern of a technology's expectations during the pre-diffusion phase (see Figure 12). The starting point of the hype cycle is the innovation trigger, the first public demonstration of new technology, from where the expectations of users and companies rise steeply until reaching its peak of inflated expectations (Fenn & Raskino, 2008). After that, innovators adopted the technology in a variety of use cases.

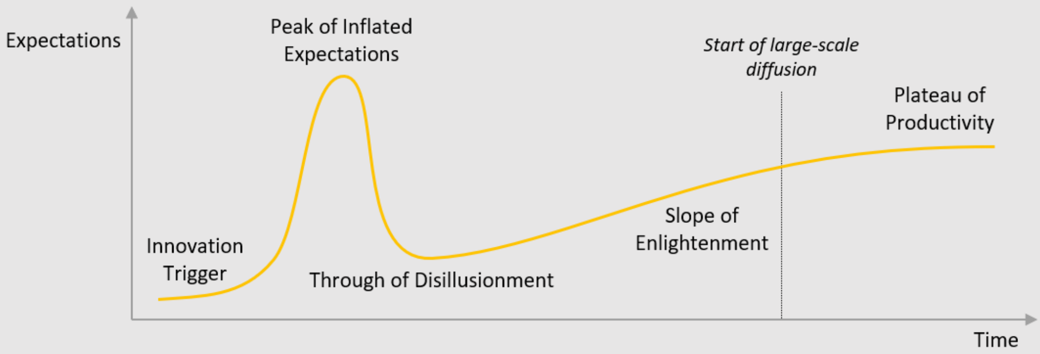


Figure 12: Gartner's Hype Cycle (adapted from Fenn & Raskino, 2008)

Afterwards, expectations fall steeply as performance issues uncover and actual use cases are limited. The technology reaches its point of disillusionment. From there, time passes, and the technology improves. Expectations increase again, and Early Adopters start using the technology during the slope of enlightenment. Then the large-scale diffusion starts, and the last phase is reached – the plateau of productivity.

Figure 13: Explanation of Gartner's Hype Cycle

As shown in Figure 13, expectations about a technology reach their peak before the large-scale diffusion starts but drop drastically again. This first increase in expectations should not be confused with the later slope of enlightenment. Additionally, one should be careful as no clear timeframes per phase have been given.

Moreover, some researchers doubt the theoretical base of the hype cycle theory mainly due to a high degree of simplification (Dedehayir & Steinert, 2016). Yet, according to the authors, they describe a phenomenon called hype dynamics, which should be included more often in theories of innovation literature.

Takeaways from the crossing the chasm branch

While most learnings from the crossing the chasm branch do not apply to the research due to its fixed emphasis on customer groups, Moore observed a few activities that might monitor the early start of diffusion. If these observations also predict the start of diffusion will be discussed in chapter 4.

3.5.2 Indicators from the crossing the chasm branch

As mentioned before, Moore has a fixed focus on customer groups during the diffusion of an innovation. However, he also described a few marketing mechanisms that might help predict the start of large-scale diffusion. An overview of the nine indicators derived from the crossing the chasm branch can be found in Table 8 at the end of the section.

Critical mass reached

The first indicator, *Critical mass reached,* is based on a somewhat vague concept. Word-of-mouth requires a critical mass of customers until it begins to work effectively (Moore, 2014). This word-of-mouth can then, subsequently, help the diffusion of a product.

However, this dichotomous indicator brings an array of problems with it. While the data source, sales data, is relatively easy to retrieve from an own company, competitors are likely to be hesitant to share their sales data, especially during the early diffusion period. Additionally, the concept of critical mass seems to make sense theoretically but from a practical standpoint defining the number of customers of a new innovation representing the critical mass seems impossible.

Number of articles in the popular media

Moore (2014) mentions various media outlets focusing on different but particular target groups: technology, trade, vertical, and business press. In my opinion, these media outlets are too specific and not in a vast quantity available. For example, it is difficult to predict the diffusion of drones based on a few articles published in the only magazine covering the model aeroplane industry in a country.

To overcome this issue, I would like to introduce the indicator *Number of articles in the popular media*. In contrast to the other media outlets, the popular media is available in a wider variety, allowing predicting better based on time series data. The market indicator is quantitative, and data can be sourced from online news services or newspaper archives.

Number of online reviews

When more customers buy a product, usually more online reviews are available at retailers. The *Number of online reviews* can be used to conclude sales data and the pattern of diffusion. However, it might be observed that online reviews in a significant quantity are only available when large-scale diffusion has already started. The market indicator is quantitative and online reviews can be found on online retailer websites like Amazon.

Number of product announcements

Companies usually use product announcements to introduce a new product into the market or major product updates. Therefore, an increasing *Number of product announcements* might signal increasing intensity of the product field and advancing diffusion. Data for the quantitative technology indicator can be found in the news section of a firm's website.

Number of product reviews in the media

Similarly to the earlier indicator number of online reviews, media outlets and professional magazines also test products and publish their reviews. However, the number of reviews will be far lower than the number of customer reviews. Still, it might be worth using such an indicator. The market indicator might predict diffusion earlier as professional reviewers tend to publish their reviews before customers start adopting a product. The professional reviews should inform customers before making a buying decision. Quantitative data can be collected from online newspapers and magazines.

Number of trade fair presentations

Companies use trade fairs to showcase their new products to other businesses and customers. Therefore, a trade fair presentation of a company could imply the readiness of a company to enter the market. Furthermore, it might show an industry's research and development intensity, indicating a soon to happen large-scale diffusion. Experts and company websites are the data source for this quantitative market indicator.

Sentiment of internet forums

Internet forums are used nowadays by various users to discuss problems, tips and to share stories. Independent individuals or companies themselves set up these internet forums to promote a community feeling. To measure and quantify the opinion of users in internet forums, a sentiment analysis can be done. The market indicator could then reflect on the opinion of early users, which might suggest diffusion if the indicator shows a positive sentiment.

Sentiment of online reviews

Professional online reviews in magazines and newspapers usually offer some scale to measure a product's performance. Additionally, a sentiment analysis of the review text could be done to identify the underlying opinion of a professional reviewer. Compared to customer reviews, the possibility of fraud by fake reviews, which might be exceptionally high during the early period of a product's life cycle, is decreased. This quantitative market indicator could suggest whether a reviewer is positive or negative towards a new product or innovation, implying a fit between customer needs and supplier offers.

Sentiment of the popular media

Likewise to the indicator before, a sentiment analysis could be done of articles in the popular media. This sentiment analysis might be especially interesting as a newspaper article does not offer a rating of the product or technology discussed, unlike a review. The indicator could reveal if the opinion or information is in favour of a technology. High expectations in the popular media could indicate that more customers start buying a product.

Table 8: Indicators derived from the crossing the chasm branch

Indicator	Data Source	Focus of Indicator	Type of Indicator
Critical mass reached	Sales data	Market	Dichotomous
Number of articles in the popular media	Online newspapers	Market	Quantitative
Number of online reviews	Retailer	Market	Quantitative
Number of product announcements	Company news	Technology	Quantitative
Number of product reviews in the media	Online newspapers, online magazines	Market	Quantitative
Number of trade fair presentations	Company news, expert opinion	Market	Quantitative
Sentiment of internet forums	Internet forums	Market	Quantitative
Sentiment of online reviews	Retailer	Market	Quantitative
Sentiment of the popular media	Online newspapers	Contextual	Quantitative

3.6 Scoping literature review: Disruptive Innovation branch

3.6.1 Introduction to the disruptive innovation branch

The term disruptive innovation has been made famous by Christensen more than 25 years ago. Since then, a variety of meanings have been interpreted into it. Initially, a disruptive innovation was defined as an inferior product or service, compared to the dominant product, which a smaller company has introduced in an overlooked market segment (Bower & Christensen, 1995). Usually, incumbents tend to increase a product's performance at a higher pace than customer demand increases. This means that incumbents will fulfil the medium to high-end market, and a gap is opened for a smaller company responding to the needs of the low-end market or an entirely new market (Christensen et al., 2015).

After many new technologies and business models, Christensen et al. (2015) revisited the theory and emphasized four learnings:

1. Disruption is a process over time
2. Disruptive business models distinguish well from incumbents
3. Not all disruptive innovations succeed
4. Incumbents should use a hybrid approach sustaining and disrupting the market in separate business units

The theory of disruptive innovation differentiates from the theories above by its inclusion of a predecessor or incumbent technology. In addition, while earlier theories only explained the technology in focus, disruptive innovation theory includes technology's satisfying similar customer needs.

Nevertheless, the disruptive innovation theory does not apply entirely to the type of innovation focused on in the thesis. Disruptive innovations are usually inferior innovations that are introduced in an overseen market segment. This definition excludes innovations aiming to replace an incumbent's product using a new technology on a similar product performance level. Thus, disruptive innovations are too narrowly specified for the use of this master thesis. Due to this reason, the research by Christensen et al. about the prediction of the industry change will not be included in the scoping literature review (cf. Christensen et al., 2004).

Takeaways from the disruptive innovation branch

Although not all radically new high-tech innovations are disruptive, we might learn something from the specific disruptive innovation branch. It may be viable to investigate a predecessor of a radically new high-tech innovation to determine when an innovation will enter the market.

3.6.2 Indicators from the disruptive innovation branch

The disruptive innovation branch is not very fruitful to derive indicators due to the earlier explained strict definition of disruptive innovations. Nevertheless, two indicators could have been derived from the branch. An overview is given at the end of the section in Table 9.

New incumbent firm entry

The disruptive innovation branch describes that mainly smaller and younger companies enter the market first with a new innovation. However, it has been shown that incumbents should not forego introducing a new innovation (Christensen et al., 2015). But incumbents are often more rigid and slow to adapt to changes while simultaneously positively affecting the customer. If an incumbent offers a new innovation, customers could be more willing to adopt an innovation because of the existing trust in the incumbent. Therefore, if an incumbent enters the market, it might signal that the diffusion starts soon. Markovitch & Golder (2008) presented a similar line of reasoning of the diffusion forecasting branch (see Section 3.2).

Predecessor's growth slows down

The central theme of the disruptive innovation branch is the separation between predecessor technology (often by an incumbent) and new technology. Therefore, it is rather apparent to include the indicator *Predecessor's growth slows down* into the preliminary list of indicators. If a predecessor's growth slows down, it might suggest that a new technology is growing in sales and customers are switching to the newer product. This would mean the large-scale diffusion of the new product would start.

Table 9: Indicators derived from the disruptive innovation branch

Indicator	Data Source	Focus of Indicator	Type of Indicator
New incumbent firm entry	Retailer	Market	Quantitative
Predecessor's growth slows down	Sales data	Contextual	Quantitative

3.7 Scoping literature review: Pre-diffusion branch

3.7.1 Introduction to the pre-diffusion branch

Similarly to the dominant design branch, where many small innovations lead to one final significant innovation entering the market, Ortt and Kamp describe a systematic pattern. In this systematic pattern, various niche products exist during a pre-diffusion phase until one major product enters the mass market. Originally the framework has been developed to decide on a type of niche strategy based on the technology innovation system (Ortt & Kamp, forthcoming). The niche introduction strategy compares well to the crossing the chasm branch, also recommending a niche strategy to enter a market. However, the framework also provides learnings about the environment in which a new innovation exists before the start of large-scale diffusion.

The pattern of development and diffusion of technological breakthroughs has three phases categorizing the different development stages of a product's diffusion (Ortt, 2010): innovation phase, adaptation phase, and the market stabilisation phase. The earlier two phases are also summarized into the pre-diffusion phase. During this time, a technology gets invented, and companies try to commercialize their innovation with a niche business model. The niche business model is characterized by focusing on a small customer group, usually Innovators of a new product type (cf. Section 3.5).

The conditions for large-scale diffusion are many times not met shortly after invention. Therefore, different niche products embody various development projects, sometimes emerging simultaneously or consecutively. On a project level, the pre-diffusion phase is also referred to as the fuzzy front-end.

According to Ortt and Kamp (forthcoming), seven building blocks and seven influencing factors hinder the mass-market introduction (see Figure 14). The building blocks categorize into social, economic, and technical factors. These factors are the main determinants of the current development state. Extending the building blocks, the influencing factors, as the name suggests, influence the core factors and technology pathway. Moreover, they give a deeper understanding of the barriers blocking large-scale diffusion.

Building blocks

1. Product performance and quality
2. Product price
3. Production system
4. Complementary products and services
5. Network formation and coordination
6. Customers
7. Innovation specific institutions

Influencing factors

8. Knowledge and awareness of technology
9. Knowledge and awareness of applications and market
10. Natural, human and financial resources
11. Competition
12. Macro-economic and strategic aspects
13. Socio-cultural aspects
14. Accidents and events

Figure 14: 14 factors for a large-scale diffusion of breakthrough technologies

Each factor has a three-point scale, similar to a traffic light reaching from slowing down large-scale diffusion to not slowing down the large-scale diffusion. Only when all core factors show a green light diffusion is not hindered and a sales take-off is possible. The influencing factors play a role in determining and explaining why a specific building block hampers diffusion.

The authors suggest that the factors indicate the timing of diffusion (Ortt & Kamp, forthcoming). However, the 14 factors of the pre-diffusion branch are relatively open categories for a qualitative assessment. Although this approach permits a high degree of generalization, allowing it to apply the theory on various cases in detailed qualitative research, prediction is more complex due to less quantification and leniently defined indicators.

Takeaways from the pre-diffusion branch

The pre-diffusion research adds to the dominant design literature by describing three distinguishable phases. Furthermore, Ortt and Kamp define 14 factors examining the technology in focus, but also the market and environment around an innovation. The 14 factors give holistic guidance in assessing and understanding the current innovation state. Although the model has been developed to formulate niche strategies, all building blocks and influencing factors are highly relevant for observing the diffusion of an innovation. They cover the environment around an innovating firm, but also the product itself. Most indicators that have been derived so far from other branches cover the majority of the 14 factors. Hence, the 14 factors will be used as categories for the indicators because of their high generalization and completeness.

3.7.2 Indicators from the pre-diffusion branch

As mentioned in the takeaways, the 14 factors provide a holistic assessment of the pre-diffusion phase. Therefore, the 14 factors will be used as categories for the already derived indicators. Before the complete overview of indicators will be given in Chapter 4, a quick assessment has shown that the category complementary products and services has not been covered by any indicator so far. The rest of the categories has already been covered quite extensively.

Complementary products and services available

Thus, *Complementary products and services available* will be the only indicator derived from the pre-diffusion branch (see Table 10). The qualitative indicator assesses if complementary products and services for the new innovation are available at retailers. These complementary products and services are most times required to use a product adequately. Hence, they should be available in a sufficient quantity and variety for customers before the start of large-scale diffusion.

Table 10: Indicators derived from the pre-diffusion branch

Indicator	Data Source	Focus of Indicator	Type of Indicator
Complementary products and services available	Retailer	Technology	Qualitative

3.8 Discussion of the Scientific branches

Section 3.2 started with a systematic literature review of predictive diffusion models. The objective of the systematic literature review was to analyse and classify existing predictive models and their indicators. Concluding the literature review shows that most models focus on predicting the demand as soon as an innovation has reached significant sales numbers. The most applied forecasting technique in the diffusion forecasting branch is the curve-fitting approach. Based on the initial sales and a predictive model, fed with technology and market variables, forecasts of the future demand are generated. These predictive models can generate accurate forecasts of future demand and are continuously improved with AI technologies and new variables. However, they do not fit entirely the research agenda of this master thesis focusing on the pre-diffusion phase. Therefore, a new approach for the thesis was needed.

I started exploring scientific branches closely connected to the diffusion literature in scoping literature reviews to develop a new forecasting approach from the ground up. The scoping literature reviews aimed to give an overview of existing approaches that observe the environment of an innovation before its diffusion. Five branches have been presented, which will be now discussed and compared.

The macroenvironment branch stands out from the other four branches because it has a more neutral environment view. While the other four branches at least describe the emergence and diffusion of an innovation, the macroenvironment branch takes a systematic perspective on the environment, not necessarily focused on the diffusion of a product.

The leading theme of the dominant design branch is the evolutionary model of technological change in which a technology moves through two distinctive eras until a new technological discontinuity emerges. The pre-diffusion phase complements the research about the shift from the fluid phase to the transitional phase, or the era of ferment, established by the dominant design branch. Both theories describe a somewhat uncertain phase in which the various alternatives emerge. However, the pre-diffusion branch uses a company perspective integrated into a broad system view to model the environment by 14 factors. On the other hand, the dominant design branch does not offer such a systematic analysis of the environment. Instead, its focus lies on the evolutionary description of technological generations.

Moore from the crossing the chasm branch takes a whole different perspective for his research. He focuses on describing behaviours and stereotypes of typical customers per phase. These constructs are challenging to measure, making prediction harder and open for bias. Researchers from the pre-diffusion phase, dominantly driven by Ortt and Kamp, focus on assessing the innovation and its environment, something of a higher value for this master thesis.

Moreover, Moore argues that the shift from the early market to the mass market is drastic and disruptive. Customers would have entirely different needs, and a different approach on the company side is needed to market a technology to the early majority instead of the early adopters. In contrast, Ortt and Kamp see the shift from the pre-diffusion phase to the mass market as less drastic. While earlier niche products might not be ready for the mass market because not all 14 factors are supportive, one of the niche products turns out to have all 14 factors ready. Hence, its mass-market diffusion starts.

Lastly, the disruptive innovation branch argues for the specific diffusion of new technologies in an overseen market segment. This entry strategy for disruptive innovations (a sub-category of the here discussed radically new high-tech innovations) is a specific type of niche strategy. This comparison shows that although each branch has a different focus, they are all somewhat similar in their core, focusing on large-scale diffusion mechanisms.

Takeaways of the scientific branches

All six literature reviews provide insights into its main theories. While not every theory is entirely relevant or necessary for deriving the observational indicators, they give observations and explanations that will be considered to a varying degree in Chapter 4. An overview of the branches and the part of the theory used can be seen in Figure 15.

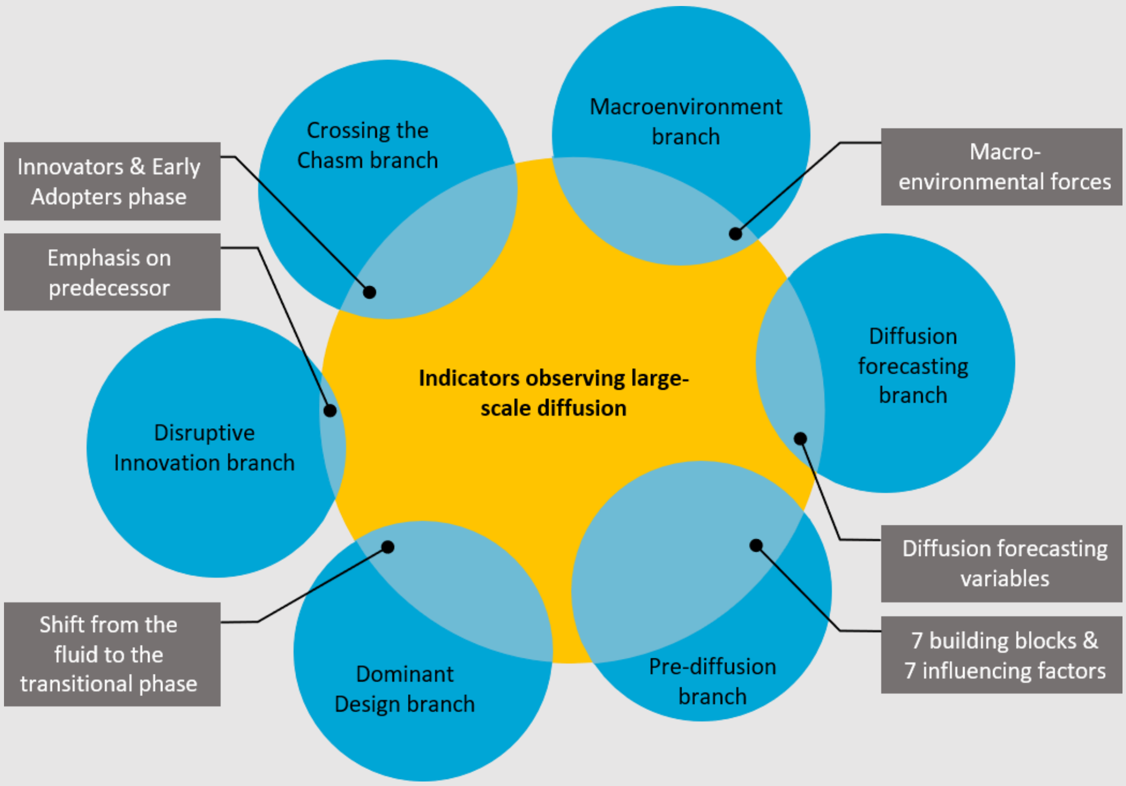


Figure 15: Overview of key takeaways per scientific branch

4 Analysis

In this chapter, the findings from the literature review will be analysed and prepared for the forecasting approach that will be designed afterwards. Various scientific branches have contributed towards a list of observing indicators (presented at the end of each literature review) that observe the start of large-scale diffusion. However, not all of these indicators might predict well enough. Therefore, the third step of the data selection funnel will be applied to narrow down the indicators towards the final list of indicators (see Section 2.1.2).

In Section 4.1, potential indicators to evaluate the indicators will be presented, discussed, and subsequently selected in the sub-sections. Afterwards, in Section 4.2, the indicators will be evaluated according to the finally selected criteria. This evaluation data will be used to perform the sensitivity analysis for five different selection mechanisms in Section 4.3. The sensitivity analysis will show how sensitive the selection mechanisms are. Additionally, the selection mechanisms will be discussed, and the most robust mechanism selected to receive the final list of indicators. Finally, the final list of indicators will close this chapter to proceed with the design of the forecasting approach, combining the indicators and the forecasting techniques, in Chapter 5.

4.1 Criteria to assess indicators

A variety of indicators have been presented in the previous section found in the literature or derived from literature. The inventory of indicators aimed to find variables from various perspectives observing the diffusion before and during its process. However, at the end of Chapter 4, a shortlist of indicators that predict the upcoming start of diffusion should exist. To reduce the inventory of indicators to the most crucial and useful one’s, criteria will be applied to sort out unnecessary and not fitting indicators.

The selection criteria will be used to sort out not relevant indicators. First, several potential criteria will be explained in Section 4.1.1. Then, in Section 4.1.2 the described criteria will be discussed, and in Section 4.1.3 the definitive criteria selected and their scale described.

4.1.1 Potential criteria

Prediction

The indicator in focus should predict directly or indirectly the upcoming diffusion of an innovation. This prediction is possible if an indicator assesses a mechanism or circumstance that impacts the technology’s trajectory to diffuse earlier or later. Compared to the earlier mentioned indicators from the diffusion literature, selected indicators should predict diffusion before the large-scale diffusion has started.

Timeliness of prediction

This criterion measures how early an indicator can predict the diffusion of an innovation.

Generalizability

The indicator should be generalizable to several innovations. A generalizable indicator would ensure that the outcome of this research applies to many industries and products, allowing a broad application of the research.

Flexibility

Another criterion to classify the indicators is their degree of flexibility. The flexibility measures by how much an indicator covers a mechanism or an actual number.

Availability of data

An indicator is only helpful if the underlying data is available to the applicant of the forecasting approach. While some data will be available publicly on the internet, other data might be only available to specific actors.

Cost of data

Data has a price. Especially nowadays when the era of data has been announced (Cai & Zhu, 2015). Some data might be offered for free, while other data will only be available behind a paywall. Moreover, some data might have to be prepared before being evaluated. This pre-processing also increases the cost of data.

Quantifiable and objectivity

This criterion measures to what degree an indicator is quantifiable and objective. Risks due to only including quantitative indicators will be discussed in the next section.

Empirical proof

The selected indicator should be scientific and based on empirical proof. While all indicators are based on a scientific theory, not all indicators have also been proven to predict the start of diffusion. This criterion assesses how well and to which extend an indicator has been proven empirically.

Simplicity

As mentioned before, pre-processing of data could apply to some indicators. This pre-processing influences the practicability of indicators and its simplicity. Additionally, some indicators might be easier to apply than others. This relatively flexible criterion might give some insights into the practicability of the predictive model and its indicators.

In the following section, the mentioned criteria will be discussed and analysed for the selected indicators.

4.1.2 Discussion of criteria

Not all of the mentioned criteria are relevant for the selection process of the indicators. Therefore, the indicators which have been explained in the earlier section will be discussed per item.

Prediction

The predictiveness of an indicator is the most crucial selection criterion of all because the main aim of the selected indicators is to forecast the start of a diffusion. Unfortunately, most indicators of the diffusion literature lack this predictive criterion as they only forecast diffusion as soon as diffusion has started. For example, Bass used a curve-fitting approach in which an S-shaped curve has been fitted to match the diffusion pattern. However, the curve fitting is only possible when diffusion has already started. Therefore, the Bass diffusion research and its indicators do not fit the developed model's objective.

Timeliness of prediction

Early into the development of an innovation, the measuring construct might be still uncertain. For example, what first seems to be a promising dominant category of a technology, turns out to be highly irrelevant as soon as the expectations and technical specifications have become more specific. However, quantitative indicators, which change annually, such as prosperity measures, might also be affected by this hindsight.

Generalizability

Indicators should be generalizable to several innovations, products and services, and industries to increase the applicability. On the other hand, some indicators can be highly relevant and predictive to only one group of innovations. Some innovation groups that could be applied to classify the indicators are:

- Business to Business products vs Business to Customer products
- Standalone product vs Reliant on complementary goods
- Standalone product vs Platform
- De facto standardization vs De jure standardization
- Product vs Service

These innovation groups are examples of a potential classification. The mentioned innovation groups are not exhaustive as they are dependent on the list of potential indicators.

Flexibility

A high degree of flexibility allows measuring developments in a closely connected construct from a similar perspective. For example, the indicator product price would score low regarding flexibility. In contrast, the indicator *Dominant design selected* would score high on flexibility as it assesses a mechanism or theory rather than a fact. A high degree of flexibility would allow measuring also concepts and ideas closely connected to an indicator allowing the indicator to apply to a wide range of use cases.

On the other hand, a highly flexible indicator might lead to uncertainty and superficial assessments of a situation. As already mentioned, for the factors of the pre-diffusion literature, some factors cover a too wide field of events reducing the comparability of technologies.

Availability of data

Availability of data is an essential selection criterion for the indicators. Indicators that rely on data that only certain actors can access are not practical for the forecasting approach.

Cost of data

On the first look, the *Cost of data* might be a criterion that correlates highly with the criterion availability of data. For example, data which is only available to subscribers of certain institutions are likely to be costly. However, this might not always be true. Some data is easy to access but might need to be pre-processed, which increases data costs. On the other hand, sales data of a previous innovation is available for free of a company's own data but due to confidentiality reasons, not of competitors or customers.

Quantifiable and objectivity

Quantitative and dichotomous indicators can directly be integrated into the forecasting approach. Qualitative concepts might be essential to grasp expert opinions. However, qualitative indicators might risk a lack of objectivity. To overcome this flaw, a Likert scale could be used to quantify pre-defined qualitative concepts.

This criterion is related to the criterion *Flexibility*. The degree of flexibility correlates negatively with the criterion *Quantifiable and Objectivity*. Moreover, the criterion *Flexibility* is too ambiguous. Hence the criterion flexibility will not be used to assess the indicators as it does not provide any further information.

Empirical proof

Indicators with empirical proof should be preferred over indicators without proof. However, it might be relevant to extend existing models by including indicators backed by a scientific theory. If a valid line of reasoning exists, these indicators can add to the existing theory and have a scientific contribution. Conversely, indicators with a lack of scientific basis should be excluded to increase the validity of the predictive model.

Simplicity

The target audience of the forecasting approach are innovation and product managers, as well as other relevant and knowledgeable employees and scientists. Nevertheless, a simple to understand indicator increases the likelihood of frequent and correct usage.

On the other hand, some indicators might be interwoven into the same construct or are connected by a relationship. Hence, they might move in the same direction due to causal reasons. While this might be vital information, more complex indicators should also be selected for the final list of indicators to grasp the holistic environment around an innovation influencing the start of diffusion.

Additionally, the simplicity of an indicator depends on the complexity of the underlying construct and the data source. For example, a quantitative indicator such as the number of patents is easily defined. However, a rather forward-looking indicator such as the potential impact of patents is more complicated to define and evaluate.

4.1.3 Selection of criteria and rating scales

Following the discussion of the criteria in the earlier section, criteria will be selected to analyse the indicators further. Criteria will be sorted after descending importance into exclusion criteria, selection criteria, and classification criteria.

For reasons provided in Section 2.1.2, the five-point itemized rating scale has been chosen. The scale is subjective. However, a description of each item per criterion scale will be provided below to increase the convergent validity.

Exclusion criteria

The *Prediction* criterion and the *Timeliness of the prediction* criterion serve as an exclusion criterion due to its high importance for the research. Therefore, every indicator without a predictive component will be excluded from further analysis. The predictive criteria will use the following itemized rating scale.

Prediction scale

- 1 point: Indicator does not predict.
- 2 points: Indicator does not predict well.
- 3 points: Unsure about predictiveness
- 4 points: Indicator predicts during the pre-diffusion phase.
- 5 points: Indicator predicts well during the pre-diffusion phase.

Unlike the other criteria, the criterion prediction will be assessed by three experts to include an external view and the long-term experience of the experts. The experts' background and expertise can be seen in Table 11.

Table 11: Background and expertise of the experts

#	Job description	Expertise	Duration of work experience
1	Associate professor at TU Delft, Netherlands	Assessing patterns for about 150 cases of radically new high-tech innovations	At least 20 years in the field of expertise
2	Assistant professor at TU Delft, Netherlands	Technology diffusion and technology innovation system	At least 20 years in the field of expertise
3	Associate professor at TU Delft, Netherlands	Standardization, business strategy, platforms, sustainable energies, and responsible innovation	At least 17 years in the field of expertise

Additionally to the *Prediction* scale, the experts have been asked about the *Empirical proof* for the indicators. The information provided has been later on merged with the assessment of the *Empirical proof* scale.

Timeliness of prediction scale

The criterion *Timeliness of prediction* uses a slightly adapted five-point itemized rating scale. The items for the criteria scale have been based upon the findings by Ortt & Schoormans (2004). However, to increase the degree of detail for the assessment, the innovation and market adaptation phases have been split into early and late items. The split between the early and late part of the innovation or market adaptation phase only exists theoretically as an assessment criterion. Practically no timepoint divides the early and late phases.

Although one might suggest that timeliness has a trade-off between "the earlier, the better" and high uncertainty in the innovation phase, this is not the case. The rule "the earlier, the better" does not apply to the pre-diffusion phase indicators. After analysing 50 innovations, the overall pre-diffusion phase takes about 17 years (Ortt, 2010). Even in the early and late market adaption phase, a prediction is still highly relevant and early enough for a company to prepare for large-scale diffusion.

Nevertheless, the data at the beginning has high uncertainty. Therefore, the points for the rating timeliness of prediction increases towards the late market adaption phase, as shown in Figure 16.

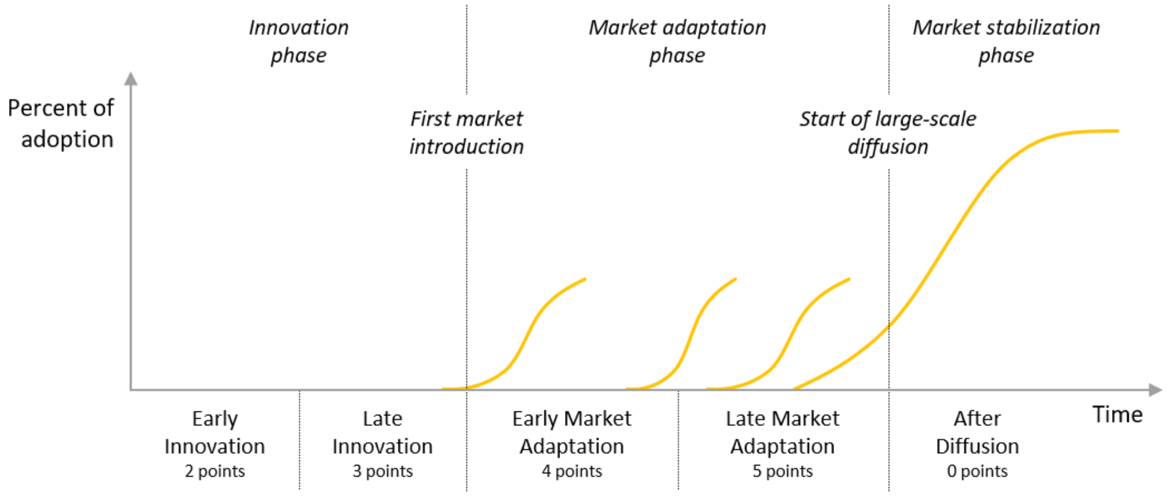


Figure 16: Rating of the criterion timeliness of prediction (adapted from Ortt & Schoormans, 2004)

The rating of the timeliness will be done with the best knowledge and belief. The itemized rating scale for the criterion *Timeliness of prediction* is as follows.

0 points: Indicator only reflects having no value for a predictive model.
2 points: Indicator predicts during the early innovation phase.
3 points: Indicator predicts during the late innovation phase.
4 points: Indicator predicts during the early market adaptation phase.
5 points: Indicator predicts during the late market adaptation phase.

Selection criteria

The following criteria will be used to select the right indicators: *Availability of data*, *Cost of data*, *Quantifiable and Objectivity*, and *Empirical proof*. Besides the exclusion criterion, these criteria have high relevance in selecting the most valuable indicators.

Availability of data scale

1 point: Data might not be available.
2 points: Data might not be readily available in large quantities.
3 points: Neutral

4 points: Data is available but must be pre-processed or derived manually.
5 points: Data is readily available in large quantities from various sources.

Cost of data scale

1 point: Data is only available after significant investments.
2 points: Data is available for a fee.
3 points: Neutral
4 points: Data is available for free but requires pre-processing by experts or software.
5 points: Data is available for free.

Quantifiable and objectivity scale

1 point: Data is based mainly on assumptions.
2 points: Data is qualitative, and the degree of subjectivity is high.
3 points: Data is qualitative but can be quantified easily with, for example, a Likert scale.
4 points: Data is quantitative but might be influenced by third parties to a small degree, such as developers of sentiment analysis software.
5 points: Data is quantitative and objective.

Empirical proof scale

1 point: No empirical proof and line of reasoning of the indicator shows flaws.
2 points: No empirical proof, but the indicator's line of reasoning is coherent.
3 points: Scientific explanation of a mechanism exists.
4 points: Empirical proof somewhat supports indicator.
5 points: Empirical proof supports indicator.

Classification criteria

The criteria *Generalizability* and *Simplicity* serve to classify the indicators. While it is not necessary to exclude, for example, too specific or too generalized indicators, it is still important information to know for the evaluation and later use of the indicators. As mentioned before, industry-specific indicators can predict well for specific innovations.

Generalizability scale

1 point: Indicator is only applicable to a specific group of innovations.
2 points: Applicability of indicator is heavily restricted to a few groups of innovations.
3 points: Neutral
4 points: Indicator applies to the majority of innovations.
5 points: Indicator applies to all kinds of innovations.

Simplicity scale

1 point: The indicator is complex and might not be answerable by users.
2 points: Effort is needed to understand the indicator and its definition, and a rating is complicated but possible.
3 points: Neutral
4 points: The notion of the indicator is somewhat easy to understand, and an answer might be given with little effort.
5 points: The notion of the indicator is easy to understand and readily answerable.

4.2 Evaluation of indicators

The results of the indicator evaluation for all indicators found in the literature reviews are shown in Table 12. The column prediction shows an average value of the three external expert evaluations (see Appendix B: Detailed indicator evaluation per expert). In contrast, the other criteria have been assessed internally by myself.

Table 12: Results from the indicator evaluation

P=Prediction; TP=Timeliness of prediction; AD=Availability of data; CD=Cost of data; Q&O=Quantifiable and objectivity; EP=Empirical proof; G=Generalizability; S=Simplicity

Indicator	P	TP	AD	CD	Q&O	EP	G	S
Frequency of product changes decreases	3,33	5	3	4	3	3	5	3
Predecessor's growth slows down	4,33	5	3	4	5	3	3	4
Dominant category selected	2,67	5	4	4	3	3	5	3
Dominant design selected	2,33	0	4	4	3	3	5	4
Number of product categories decreases	3,00	4	4	5	3	3	5	4
Standards exist	3,00	4	5	5	5	3	4	5
Complementary products and services available	4,67	5	4	5	3	3	3	3
A problem to be solved exists	3,33	3	2	2	2	2	5	1
Critical mass reached	3,33	5	2	3	2	3	5	2
Sentiment of internet forums	3,67	5	4	4	4	3	2	4
Size of the market	3,33	0	3	4	4	5	5	4
Bandwagon effect	4,00	5	3	3	2	3	5	3
Network externalities	4,00	5	3	3	2	3	4	3
Associations, coalitions, or groups formed	3,67	3	3	5	3	3	3	4
Laws and Regulation	2,67	5	4	5	2	3	3	3
Identified as a megatrend	4,00	3	3	3	1	3	5	5
Number of articles in the popular media	3,67	4	5	5	5	3	4	5
Certain customer requirements	4,67	5	3	4	2	3	5	3
Bibliometric data	4,00	3	4	4	5	5	5	5
Certain product specifications	4,33	5	3	4	2	3	5	4
Development effort and capabilities	3,33	3	2	4	4	5	5	3
Education	3,33	2	3	3	3	2	5	2
Forward citations of patents	4,33	4	4	4	5	5	5	4
Novelty of the patent	3,33	3	4	4	5	5	5	5
Patent growth speed	4,33	3	4	4	5	5	5	5
Quality of patents	3,33	3	4	4	2	5	5	3
Quantity of patents	4,00	3	4	4	5	5	5	5
Science-intensity	3,33	3	4	4	5	5	5	5
Scope and coverage of patents	3,67	3	4	4	5	5	5	5
Abnormal stock returns	4,00	5	5	5	5	5	4	5
Purchasing power	3,33	5	5	5	5	3	5	5
Coefficient of innovation	3,33	0	3	4	3	5	5	4
Availability of materials, suppliers, etc	3,67	3	4	4	3	3	4	4
Number of product announcements	4,33	4	5	5	5	3	5	5
Number of trade fair presentations	4,67	4	4	5	5	3	4	4

Table 12 (continued)

Coefficient of imitation	4,00	0	5	5	3	5	5	5
New firm entry	4,33	4	4	5	5	5	5	5
New incumbent firm entry	3,67	5	4	5	5	5	5	5
Market penetration	2,33	0	5	5	5	5	5	5
Year of introduction	2,00	0	5	5	5	5	5	5
Sentiment of the popular media	4,33	4	4	4	4	2	4	4
Number of online reviews	3,67	5	5	5	5	3	3	5
Number of product reviews in the media	4,00	4	5	5	5	3	4	5
Sentiment of online reviews	3,67	5	4	4	4	3	3	4
Product performance increases	4,67	5	5	5	5	3	5	4
Product price decreases	3,67	5	5	5	5	4	5	5
Switching costs	1,67	5	3	4	4	3	4	4
Automatization of production increases	3,33	5	1	3	3	3	4	3
Production capacity increases	3,33	5	2	3	5	3	4	4
Supportive niche communities	2,67	5	3	3	3	3	4	3

To clarify the evaluation, the process and decisions will be explained on the example of the indicators *Frequency of product changes decreases*, *A problem to be solved exists*, and *Abnormal stock returns*. The first indicator in the list received an average rating. This example follows an indicator with a below-average rating and an indicator with an above-average rating.

Exemplary rating of the indicator *Frequency of product changes decreases*

The experts have rated the indicator's predictiveness with a 3,33. Two experts said that a decrease in the product changes shows an advanced stage in the product development process. Companies would start focusing and further develop only the most potential product candidates. The third expert claimed that product changes would slow down too late in the product lifecycle and are not connected to the start of large-scale diffusion.

In my opinion, a slower frequency of product changes still happens before the start of large-scale diffusion. However, such a development would only be visible late in the pre-diffusion phase. Hence the indicator received a rating of five for the criterion timeliness of prediction.

Availability of data and *Cost of data* has been rated with a three and four, respectively. Regarding the *Availability of data*, a neutral rating has been given. It depends primarily on whether various product types are available and if changes can be tracked over time. However, if data is available, costs are relatively low. Information about a product's features and design can be retrieved for free at various online retailers. However, an expert is required to judge what a significant product change is. Only afterwards, the frequency can be calculated.

For the criterion *Quantifiable and Objectivity*, a three has been rewarded. The indicator largely depends on an expert's qualitative assessment of what precisely a significant product change is. Hence, the indicator is subjective, although the frequency is measured quantitatively.

The indicator is based upon a mechanism of the dominant design literature. However, the indicator has not been found applied in another forecasting model. Therefore, the indicator has been rated with a three regarding its *Empirical proof*.

The indicator has been rated with a five and three, respectively, in the classification criteria *Generalizability* and *Simplicity*. This is because the frequency of product changes can be calculated for a variety of innovations. However, the indicator is not straightforward, and an expert is required for the assessment. Consequently, the indicator received an average value for its simplicity.

Overall, the indicator *Frequency of product changes decreases* receives an average rating compared to the other indicators in Table 12.

Exemplary rating of the indicator *A problem to be solved exists*

The indicator *A problem to be solved exists* also received a rating of 3,33 for the criterion *Prediction*. Two of the experts were doubtful if the indicator would predict. Hence, they gave a rating of three. The third expert was more optimistic and gave a rating of four as the expert expected that an existing problem would create demand, leading to a large-scale diffusion.

Compared to the previous indicator, a problem to be solved emerges during the innovation phase. When a technology gets more specific, a case of application is found. This case of application translates to the indicator *A problem to be solved exists*. Therefore, the indicator received a rating of three, meaning an emergence of the indicator in the late innovation phase.

The *Cost* and *Availability of data* for the indicator are heavily constrained. To measure the construct of the indicator well, customer focus groups are required to confirm the existence of a problem. Additionally, these customer focus groups are more expensive than the previous indicator's data. Hence, in both criteria, the indicator *A problem to be solved exists* receives a rating of two.

Due to the reliance on customer focus groups, the quantification and objectivity of the indicators are hampered. For example, compared to the indicator *Abnormal stock returns*, a well-performing indicator in this criterion, customers may give subjective answers regarding a problem they perceive. Therefore, the indicator receives a low rating of two for the criterion *Quantifiable and Objectivity*.

Additionally, the empirical proof for the indicator is not solid. The indicator stems from the macroenvironment branch. However, the branch does not explain such an indicator directly. Instead, the indicator has been derived from the branch's findings based upon a line of reasoning provided in Section 3.3.2. This lack of direct empirical proof means a rating of two on the *Empirical proof* scale.

For the classification criteria *Generalizability* and *Simplicity*, the indicator receives a rating of five and one, respectively. The indicator applies to all kinds of innovations, including business and consumer products and services. Nevertheless, the indicator's line of reasoning is not simple and requires an expert with a complete understanding of the underlying construct to interview the focus groups.

The indicator *A problem to be solved exists* is one of the worst-performing indicators (compare Table 12). The indicator has a severe lack of objectivity, empirical proof and faces data-related issues. The selection mechanism described in the next section will decide if the indicator is still good enough for the forecasting approach.

Exemplary rating of the indicator *Abnormal stock returns*

As mentioned before, the indicator *Abnormal stock returns* is one of the best performing indicators in the evaluation. To begin with, the indicator received an average rating of four by the three experts. Two experts were confident that the indicator predicts or predicts well, while the third expert was unsure about the indicator's predictiveness.

The indicator is only relevant close to the large-scale diffusion. Investors tend to invest in companies that have a new promising technology. Therefore, *Abnormal stock returns* could mean that a company will soon launch an innovation that will start large-scale diffusion. Therefore, the indicator has been evaluated with a rating of five for the criterion *Timeliness of prediction*.

Also, the indicator has received the highest rating for the criteria *Availability of data*, *Cost of data* and *Quantifiable and Objectivity*. Numerical data is available for free on stock market websites for all companies traded publicly. Therefore, no costs occur, availability is not restricted, and the data is objective.

The indicator stems from a forecasting model found in the diffusion branch literature review. According to the *Empirical proof* scale, this means a rating of five is awarded because the indicator has already been used successfully in another diffusion-related forecasting model.

For the classification criteria *Generalizability* and *Simplicity*, the indicator got a rating of four and five, respectively. As mentioned before, *Abnormal stock returns* can only be calculated for companies with stocks on the market, somewhat restricting the generalizability. Nevertheless, the indicator is simple. No issues are known about the simplicity of the indicator.

Compared to the other indicators, the indicator *Abnormal stock returns* has an above-average rating. In six out of eight criteria, the indicator has received the highest rating. The remaining criteria, *Prediction* and *Generalizability*, have been evaluated with the second-highest possible rating.

This short explanation of the indicator ratings *Frequency of product changes decreases*, *A problem to be solved exists*, and *Abnormal stock returns* should give transparency to the rating process. In the next section, indicators will be selected based on the overall points they received. After this final selection step, the remaining indicators will be incorporated into the forecasting approach.

4.3 Selection of predictive indicators

The selection and exclusion criteria are highly important for the final selection of the predictive indicators. In addition, to further increase the selection's robustness, a sensitivity analysis will be performed in Excel despite the previous efforts.

4.3.1 Alternatives of selection mechanisms

Five alternatives (Excel formulas are given below, abbreviations are used according to Table 12) to calculate an overall value will be explained and compared in the following sections. This comparison aims to avoid excluding an indicator arbitrarily because of a selection error but exclude an indicator correctly based upon a bad rating in the selection criteria.

For this sensitivity analysis, five different selection mechanisms will be explained, and their results compared. The calculated values per alternative can be found in Appendix C: Results from the sensitivity analysis. First, these results will be compared to ensure the robustness of the selection mechanisms. If somewhat similar results occur, the robustness of the system is guaranteed. Next, as one mechanism must be selected, the most theoretically sound mechanism will be used. Then, this mechanism will be used for the final selection of the indicators.

Each version has a cut-off value. If the overall value, calculated by the selection mechanism, lies below the cut-off value, the indicator is excluded. The purpose of this cut-off value is to include only the most potential indicators in the final list. A potential indicator is defined as an indicator that has received a neutral rating on average in all criteria. This definition means that doubtful indicators with a neutral rating are included in the final list alongside very well rated indicators. However, the final list of indicators aims to present possibly working indicators. Therefore, insofar indicators predict in detail needs to be researched separately (see Section 7.3.2).

Version 1

$$= IF(AND([@P] >= 3;\ [@[TP]] > 0);\ SUM(Table[@[TP]:[EP]]);0)$$

The criterion *Prediction* must have a value greater than or equal to three, and the criterion *Timeliness of prediction* a value greater than zero. Otherwise, the indicator is excluded. To calculate the overall value, the columns *Timeliness of prediction*, *Availability of data*, *Cost of data*, *Quantifiable & Objectivity*, and *Empirical proof* are summed. Indicators with an overall value lower than 15 (in each of the five summed up criteria a neutral rating) will be excluded. This version, however, creates bias by assessing the criterion *Timeliness of prediction* twice.

Version 2

$$= IF(AND([@P] >= 3;[@[TP]] >= 3);SUM(Table[@[AD]:[EP]]);0)$$

The criterion *Prediction* and *Timeliness of prediction* must have a value greater than or equal to three. Otherwise, the indicator is excluded. To calculate the overall value, the columns *Availability of data, Cost of data, Quantifiable & Objectivity*, and *Empirical proof* are summed. Compared to Version 1, the criterion *Timeliness of prediction* is not included in the sum. This is because it has already been assessed as an exclusion criterion to reduce the bias mentioned in Version 1.

Additionally, the minimal expected value for the criterion *Timeliness of prediction* has been increased to three. A minimal rating of three excludes indicators directly after the invention. Indicators in this period are usually too uncertain. This uncertainty would decrease the overall reliability of a forecast. To increase the overall reliability, indicators from the early innovation phase have been excluded. Indicators with an overall value below 12 (in each of the four summed up criteria a neutral rating) will be excluded.

Version 3

$$= IF([@P] >= 3; SUM(Table[@[TP]:[EP]]); 0)$$

The criterion *Prediction* must have a value greater than or equal to three. Otherwise, the indicator is excluded. For the overall value, the columns *Timeliness of prediction, Availability of data, Cost of data, Quantifiable & Objectivity*, and *Empirical proof* are summed. Similarly as Version 2, Version 3 overcomes the bias of assessing the criterion *Timeliness of prediction* twice. However, indicators that predict too early or after the diffusion are not automatically sorted out by the selection mechanism. This missing exclusion could create a problem if such an indicator is finally selected. Therefore, indicators with an overall value below 15 (in each of the five summed up criteria a neutral rating) will be excluded.

Version 4

$$= SUM(Table[@[TP]:[EP]]) * [@P]$$

Version 4 puts more weight on the externally assessed criterion *Prediction* than the previous versions. For the overall value, the columns *Timeliness of prediction, Availability of data, Cost of data, Quantifiable & Objectivity*, and *Empirical proof* are summed and multiplied by the *Prediction* criterion. Indicators with an overall value lower than 45 (in each of the five summed up criteria and the Prediction criterion a neutral rating) will be excluded. However, the criterion *Timeliness of prediction* is not assessed separately. This lack of a separate assessment could mean that theoretically, an indicator that does not predict (*Timeliness of prediction* equal to zero) is included in the final list of indicators.

Version 5

$$= IF([@[TP]] >= 3; SUM(Table[@[AD]:[EP]]) * [@P]; 0)$$

Version 5 works similarly to Version 4. However, it excludes the criterion *Timeliness of prediction* from the sum. It checks it beforehand to avoid including an indicator in the final list which does not predict or predicts too early, increasing the overall uncertainty of the prediction. The criterion *Timeliness of prediction* must have a value greater than or equal to three. Otherwise, the indicator is excluded. The columns *Availability of data, Cost of data, Quantifiable & Objectivity*, and *Empirical proof* are summed and multiplied by the criterion Prediction for the overall value. Indicators with an overall value below 36 (in each of the four summed up criteria and the *Prediction* criterion a neutral rating) will be excluded.

Conclusion

In Appendix C, it can be seen that each version excludes somewhat similar indicators, with a few exceptions, due to close to insufficient ratings. In no case, an unexpected indicator with a usually high rating in each of the criteria is excluded. The low discrepancy between the mechanisms proves the low sensitivity towards the actual selection mechanisms. This means that the decision if an indicator is included in the final list or not relies mainly on the rating of an indicator and not the selection mechanism itself. Next, the most theoretically sound selection mechanism needs to be chosen.

Although the differences between the mechanisms are minimal, one of the alternatives must be selected.

Generally, Versions 4 and 5 are preferred due to their emphasis on the criterion *Prediction*. The criterion *Prediction* is a central scientific quality gate (see Section 2.1.3). Therefore, a high emphasis on the criterion is preferred over the other alternatives. Due to the multiplication with the criterion *Prediction*, an indicator can still be included because of a strong external rating in predictiveness, although the other criteria underperform. Practically this means that an indicator will be included if the experts have seen the potential of an indicator, although I have not seen the same potential while evaluating the other criteria.

However, Version 4 does not check the criterion *Timeliness of prediction* separately but includes it into the overall value. In contrast, Version 5 includes a pre-check of the timeliness and excludes indicators that predict too early, due to uncertainty, or occur too late, after the diffusion. Additionally, a summing up of the criterion *Timeliness of prediction* is not advisable. Higher points in this criterion do not directly translate to a better indicator. The indicator just emerges later in the pre-diffusion phase (compare Timeliness of prediction scale in Section 4.1.3). Therefore, the choice for the selection mechanism falls on Version 5. Version 5 has a decent emphasis on the criterion *Prediction* but excludes indicators that predict after diffusion or too early. Furthermore, indicators that have been assessed highly by the experts but low by myself are given an opportunity and are not excluded due to my sole opinion.

The following section shows the remaining indicators left over after the application of the selection mechanism Version 5.

4.3.2 Two sets of predictive indicators

After applying the selection mechanism Version 5, 38 out of 50 indicators were left. The other indicators had an insufficient rating because they were below the cut-off value. Indicators that can forecast the upcoming large-scale diffusion of a radically new high-tech innovation are shown in Figure 17.

Indicators left after the final selection

Frequency of product changes decreases, Dominant category selected, Number of product categories decreases, Complementary products and services available, Bandwagon effect, Network externalities, Associations, coalitions, or groups formed, Laws and Regulation, Identified as a megatrend, Certain customer requirements, Certain product specifications, Availability of materials, suppliers, etc, Quality of patents, Predecessor's growth slows down, Standards exist, Sentiment of internet forums, Number of articles in the popular media, Bibliometric data, Development effort and capabilities, Forward citations of patents, Novelty of the patent, Patent growth speed, Quantity of patents, Science-intensity, Scope and coverage of patents, Abnormal stock returns, Purchasing power, Number of product announcements, Number of trade fair presentations, New firm entry, New incumbent firm entry, Sentiment of the popular media, Number of online reviews, Number of product reviews in the media, Sentiment of online reviews, Product performance increases, Product price decreases, and Production capacity increases

Figure 17: Indicators left after the final selection

The indicators must be split into two groups to prepare the combination of the forecasting techniques and the predictive indicators. The literature review about forecasting techniques has shown that forecasting techniques can be generally split into four categories (see Section 3.1). However, one main difference exists between the four categories, which is highly relevant for matching the indicators. While truly judgemental techniques require a minimum of one expert to assess the situation around an innovation, the other techniques of the categories time series & regression modelling and machine learning techniques do not require an expert for the innovation in focus. However, this should not be confused with an expert for data science that sets up and calculates the forecasting technique.

Therefore, the indicators will be split into two groups: judgemental indicators and non-judgemental indicators. Judgemental indicators require a minimum of one expert to assess the environment around an innovation and the innovation itself. The non-judgemental indicators can be rated by an average employee and do not require expert knowledge about the innovation in focus. This differentiation can be easily made based on the criterion *Quantifiable and Objectivity* (rating higher than three is a non-judgemental indicator). The criterion has already assessed the influence an expert has on the indicator assessment. The mapping between the forecasting techniques and their indicator sets can be seen in Table 13.

The analogous forecasting method, as a unique judgemental method, stands out as both judgemental and non-judgemental indicators are recommended to find the best match between two similar innovations. Whether judgemental or non-judgemental indicators are used for analogous forecasting, an expert is required to match two innovations.

Table 13: Forecasting techniques and their indicators

Forecasting technique	Set of Indicators
Assumptions-based modelling	Judgemental indicators
Delphi method	Judgemental indicators
Analogous forecasting	Judgemental & non-judgemental indicators
Time series & regression models	Non-judgemental indicators
Artificial neural network	Non-judgemental indicators

The following two sections will present and analyse the judgemental and non-judgemental indicators, respectively.

Judgemental indicators

Judgemental indicators are all indicators with a rating of the criterion *Quantifiable and Objectivity* of three and lower. A rating of three and lower on the *Quantifiable and Objectivity* scale means that an expert of the innovation in focus influences the assessment of the indicator. An overview of the judgemental indicators is given in Figure 18. 13 out of 38 indicators are judgemental.

Judgemental indicators

Frequency of product changes decreases, Dominant category selected, Number of product categories decreases, Complementary products and services available, Bandwagon effect, Network externalities, Associations, coalitions, or groups formed, Laws and Regulation, Identified as a megatrend, Certain customer requirements, Certain product specifications, Availability of materials, suppliers, etc, and Quality of patents

Figure 18: Judgemental indicators

Most judgemental indicators are highly generalizable to a variety of cases. Only the indicators *Complementary products and services available, Associations, coalitions, or groups formed*, and *Laws and Regulation* are restricted in their applicability to lesser cases. The inclusion of these indicators has to be done on a case-by-case basis. On average, judgemental indicators score medium on the *Simplicity* scale. This means that the experts require some effort to understand and rate an indicator.

On average, the judgemental indicators have received a rating of 47,8 points out of 100 possible points. However, this relatively medium performance can be explained due to the maximum possible rating of three for the criterion *Quantifiable and Objectivity*, lowering the maximum possible points for the judgmental indicators to 90. The best performing indicator is *Complementary products and services available* with 70 points because of its high rating in the criteria *Prediction, Availability of data* and *Cost of data*. The two worst indicators are *Laws and Regulation* and *Dominant category selected* with each 37,3 points. Especially the low rating in the criterion *Prediction* underperformed the otherwise decent rating in the other criteria. Another remarkable finding is that all indicators, except the indicator *Quality of patents*, are new and have been derived from the literature in Chapter 3. This observation necessarily does not mean that the indicators are wrong. However, the judgemental indicators should be used carefully.

Non-judgemental indicators

In contrast to the judgemental indicators, non-judgemental indicators have a rating of the criterion *Quantifiable and Objectivity* of four and higher. These ratings mean that no expert is required to assess an innovation with a non-judgemental indicator. An overview of the non-judgemental indicators is given in Figure 19. 25 indicators out of 38, roughly two thirds, are non-judgemental indicators.

Non-judgemental indicators

Predecessor's growth slows down, Standards exist, Sentiment of internet forums, Number of articles in the popular media, Bibliometric data, Development effort and capabilities, Forward citations of patents, Novelty of the patent, Patent growth speed, Quantity of patents, Science-intensity, Scope and coverage of patents, Abnormal stock returns, Purchasing power, Number of product announcements, Number of trade fair presentations, New firm entry, New incumbent firm entry, Sentiment of the popular media, Number of online reviews, Number of product reviews in the media, Sentiment of online reviews, Product performance increases, Product price decreases, and Production capacity increases

Figure 19: Non-judgemental indicators

Overall, the non-judgemental indicators have received 67 points out of 100 possible points. The worst performing indicator is the indicator *Production capacity increases*. This overall low rating can be explained mainly due to the low rating in the criteria *Cost and Availability of data*. The three best performing indicators are *Product performance increases, New firm entry*, and *Abnormal stock returns* with 84, 82, and 80 points, respectively. In most criteria, the top three indicators have received a rating of four and higher.

Generally, non-judgemental indicators are relatively easy to apply because of their high rating in the criterion *Simplicity*. Regarding their *Generalizability*, most indicators are widely applicable. However, the indicators *Predecessor's growth slows down, Number of online reviews, Sentiment of online reviews*, and *Sentiment of internet forums* are somewhat restricted in their application. Especially the last three indicators only apply to consumer products. Moreover, the *Availability of data* for the indicators *Development effort and capabilities* and *Production capacity increases* is strongly constrained due to company confidentiality.

Half of the non-judgemental indicators have already been successfully applied in other diffusion prediction models. The other half of the non-judgemental indicators are new and derived from mechanisms described in the scientific literature. Only one indicator, *Sentiment of the popular media*, has received a rating of two in the criterion *Empirical proof*. However, the indicator received an average rating of 4,33 from the scientific experts. Moreover, other indicators based upon a sentiment analysis have already shown superior results for diffusion forecasting models (see Section 3.2).

The prediction approach will combine the judgemental and non-judgemental indicators with their respective forecasting technique in the next chapter.

5 Forecasting approach

This chapter will present the forecasting approach, which guides practitioners and researchers in choosing an adequate forecasting technique for their situation. Additionally, indicators will be recommended per forecasting technique as a starting point for the prediction. The approach aims to guide a user in the lowest possible number of questions towards a forecasting technique that gives the user the highest reliability based on his answers.

The forecasting approach (see Figure 20) is divided into two stages: (i) the regular stage and (ii) the enhanced stage. In the first stage, a user of the forecasting approach is guided to choose one of the five forecasting techniques relevant to predict the start of large-scale diffusion by answering questions (see Section 3.1.5). Each of the methods has a recommended set of indicators the user should utilize for the prediction. A preview of the combination has already been shown in Table 13.

A disclaimer has been added after the validation that if a user chooses to stop in the first stage with the Delphi method or Assumptions-based modelling, the recommended judgemental indicators miss out on five categories compared to the non-judgemental indicators (see Section 6.1.2). In such a case, it is recommended to include non-judgemental indicators for these five categories to complete the holistic assessment of the situation. Non-judgemental, if only required for one time point, are relatively easy to research. Therefore, an addition of these indicators is highly recommended.

Four out of the five methods can be enhanced by implementing a hybrid approach in the second stage. The analogous forecasting is excluded from the enhancement due to its distinctive nature. Analogous forecasting already uses all available indicators in the final list, and an enhancement by combining methods does not improve the method. Instead, the method relies on an expert judging two innovations as similar enough.

The other four methods are combined so that the advantages of the second method cancel out the disadvantages of the first method (compare Cho, 2013). Most times, the improvement is made by increasing the number of indicators and data or reducing the bias by changing the analysis method. Out of the 12 possible combinations, eight combinations will be used. The other combinations are flawed because of similarities among the techniques. Overall, this will result in 13 different techniques a user can choose from, combining the first and second stage. Each forecasting technique has its advantages and disadvantages, which will be explained in the following sections.

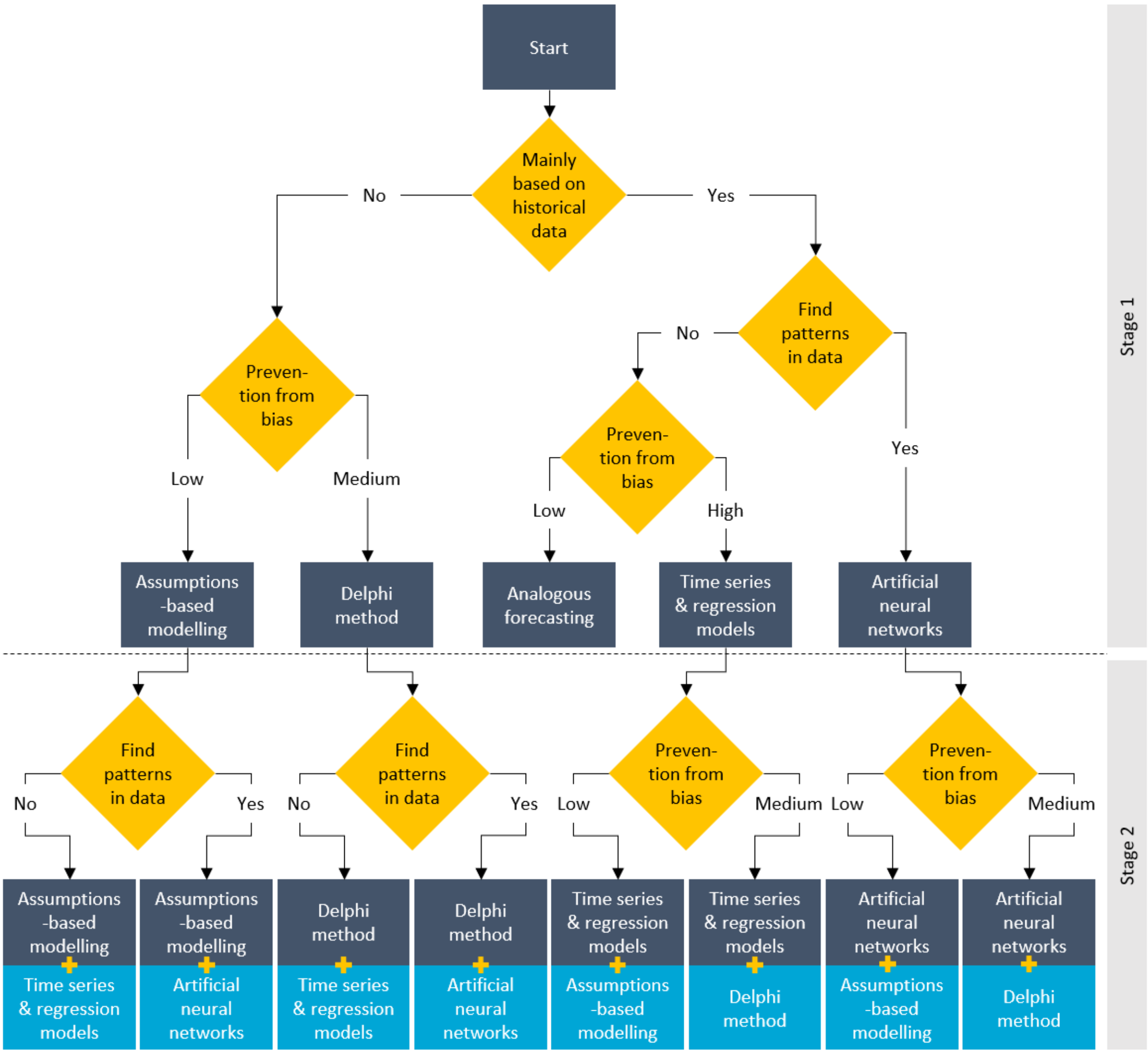


Figure 20: Forecasting approach

5.1 First stage

In the first stage, the primary method for the prediction will be found. Five methods are available, and a user will be guided towards one of the methods based on the answers given. Each of these methods works differently, and based on its characteristics, a set of indicators will be recommended. The advantages and disadvantages will be discussed in the following sections. An overview of the different techniques and how they work has already been given in Chapter 3.1.

5.1.1 Assumptions-based modelling

Advantages

Assumptions-based modelling is a judgemental approach in which the prediction is based upon judgemental indicators (see Figure 21). As discussed earlier in Section 3.1.1, these indicators can uncover information that is not represented by quantitative indicators. The main advantage of assumptions-based modelling over the Delphi method is the fast and easy process of gathering judgemental data because of the missing approach of "structured communication" (Mas-Machuca et al., 2014, p. 7) in the assumptions-based modelling.

Disadvantages

Unlike the non-judgemental methods, no historical case studies are required (Kahn, 2010). No historical cases also means that no comparison to earlier patterns of diffusion is made. While this might be a disadvantage usually because learnings from earlier cases are ignored, it might be advantageous if the case in focus is a particular case that has not occurred so far. The prediction is not changed just because the predicted value seems unusual.

Nevertheless, the bias will be high because only judgemental indicators are used (Mas-Machuca et al., 2014). The indicators' rating is influenced by the experts' personal preferences, an expert's bold personality, or individual knowledge discrepancy. Especially the last issue is of importance if one expert possesses knowledge the other experts do not have, and an average rating of an indicator is calculated (compare Mas-Machuca et al., 2014). A single outlying rating might be disregarded amongst the other expert’s ratings due to the calculation of the average.

After the validation, it was found that the judgemental indicators miss out on five categories required for a holistic assessment of the situation (see Section 6.1.2). It is recommended to add the non-judgemental indicators of these categories for a complete assessment. No expert is required to assess the indicators. Information is relatively readily available due to the nature of the indicators.

Indicators for the assumptions-based modelling *No historical cases required*

Frequency of product changes decreases, Dominant category selected, Number of product categories decreases, Complementary products and services available, Bandwagon effect, Network externalities, Associations, coalitions, or groups formed, Laws and Regulation, Identified as a megatrend, Certain customer requirements, Certain product specifications, Availability of materials, suppliers, etc, and Quality of patents

Recommended non-judgemental indicators for missing categories

New firm entry, New incumbent firm entry, Number of product announcements. Number of trade fair presentations, Number of online reviews, Number of product reviews in the media, Sentiment of online reviews, Product performance increases, Sentiment of the popular media, Product price decreases, Abnormal stock returns, and Purchasing power

Figure 21: Indicators for the assumptions-based modelling

5.1.2 Delphi method

Advantages

The Delphi method only uses judgemental indicators (see Figure 22), which have a high potential for radically new high-tech innovations (Mas-Machuca et al., 2014). Furthermore, the Delphi method does not require a database of historical case studies. So far, the method is similar to the assumptions-based modelling. However, as described before in Section 3.1.1, the model takes a different approach for the collection of data. Due to the round-based anonymous indicator rating, the bias towards a bolder personality among the experts is reduced. Additionally, knowledge between rounds is shared among the experts, allowing them to draw conclusions based on similar information. This information sharing further reduced the bias.

Disadvantages

Although measures have been implemented into the Delphi method to reduce the bias, the method is not bias-free. The forecasting technique is based upon objective indicators introducing bias into the forecast (Mas-Machuca et al., 2014). A personal preference of an expert or a group of experts might slightly alter the method's outcome.

Moreover, due to the lack of historical case studies, comparisons and learnings from earlier cases are not integrated into the prediction process. While the lack of historical cases has already been described as an advantage excluding the initial lengthy data collection, learnings from prior cases might be crucial in understanding the diffusion of an innovation in focus (Kahn, 2010).

After the validation, it was found that the judgemental indicators miss out on five categories required for a holistic assessment of the situation (see Section 6.1.2). It is recommended to add the non-judgemental indicators of these categories for a complete assessment. No expert is required to assess the indicators. Information is fairly easily available due to the nature of the indicators.

Indicators for the Delphi method *No historical cases required*

Frequency of product changes decreases, Dominant category selected, Number of product categories decreases, Complementary products and services available, Bandwagon effect, Network externalities, Associations, coalitions, or groups formed, Laws and Regulation, Identified as a megatrend, Certain customer requirements, Certain product specifications, Availability of materials, suppliers, etc, and Quality of patents

Recommended non-judgemental indicators for missing categories

New firm entry, New incumbent firm entry, Number of product announcements. Number of trade fair presentations, Number of online reviews, Number of product reviews in the media, Sentiment of online reviews, Product performance increases, Sentiment of the popular media, Product price decreases, Abnormal stock returns, and Purchasing power

Figure 22: Indicators for the Delphi method

5.1.3 Analogous forecasting

Advantages

The main advantage of analogous forecasting compared to the regression models is the reliance on a unique historical case instead of a calculated formula based on possibly contradicting historical cases (Mas-Machuca et al., 2014). This approach might be advantageous if a similar technology in a similar scenario can be found based on the assumption that the future is like the past if a similar scenario exists. The judgemental and non-judgemental indicators shown in Figure 23 can be used to show that two innovations are analogous.

Disadvantages

As already suggested in the advantages, reliance on only one historical case might be an issue if no matching case can be found or the indicators that assess if two cases match are incomplete. In the latter case, two innovations, defined by experts as equal, are in fact different because the indicators did not measure the inequalities as the list of indicators was incomplete. Additionally, the time to collect the data for the historical cases should not be underestimated.

Indicators for the analogous forecasting *Large variety of historical cases required*

Frequency of product changes decreases, Dominant category selected, Number of product categories decreases, Complementary products and services available, Bandwagon effect, Network externalities, Associations, coalitions, or groups formed, Laws and Regulation, Identified as a megatrend, Certain customer requirements, Certain product specifications, Availability of materials, suppliers, etc, Quality of patents, Predecessor's growth slows down, Standards exist, Sentiment of internet forums, Number of articles in the popular media, Bibliometric data, Development effort and capabilities, Forward citations of patents, Novelty of the patent, Patent growth speed, Quantity of patents, Science-intensity, Scope and coverage of patents, Abnormal stock returns, Purchasing power, Number of product announcements, Number of trade fair presentations, New firm entry, New incumbent firm entry, Sentiment of the popular media, Number of online reviews, Number of product reviews in the media, Sentiment of online reviews, Product performance increases, Product price decreases, and Production capacity increases

Figure 23: Indicators for the analogous forecasting

5.1.4 Time series & regression models

Advantages

The time series & regression models only use non-judgemental indicators (see Figure 24). This selection of criteria reduces the bias introduced into the forecast to a minimum because experts are not required to assess an indicator. Additionally, data from historical time points are used to calculate the regression.

Disadvantages

One major disadvantage is the lack of judgemental indicators. Although judgemental indicators introduce bias, the value outperforms the costs of bias (Mas-Machuca et al., 2014). Another disadvantage is the initial time required to collect the data. Instead of separate cases, data from different time points of the innovation in focus is required. This data collection still costs time and might be tedious during the innovation phase, where publishing is still scarce. Lastly, time series & regression models are sometimes seen as too naïve because a standardized behaviour is expected (Cho, 2013).

Indicators for the time series & regression models	*Data from historical time points required*
Predecessor's growth slows down, Standards exist, Sentiment of internet forums, Number of articles in the popular media, Bibliometric data, Development effort and capabilities, Forward citations of patents, Novelty of the patent, Patent growth speed, Quantity of patents, Science-intensity, Scope and coverage of patents, Abnormal stock returns, Purchasing power, Number of product announcements, Number of trade fair presentations, New firm entry, New incumbent firm entry, Sentiment of the popular media, Number of online reviews, Number of product reviews in the media, Sentiment of online reviews, Product performance increases, Product price decreases, and Production capacity increases	

Figure 24: Indicators for the time series & regression models

5.1.5 Artificial neural networks

Advantages

The main advantage of artificial neural networks is finding patterns in historical data (Kahn, 2010). This pattern-finding increases the reliability and overcomes the disadvantage of regression models being too naïve. Additionally, the bias of the method is low because it only relies on objective indicators.

Disadvantages

Artificial neural networks require large amounts of training data to prepare the forecasting algorithms to find the patterns (see Section 3.1.4). Data from various historical cases but also from different time points per case are needed. Therefore, the time to collect the data might be extended.

Similarly to the regression models, artificial neural networks do not use judgemental indicators (see Figure 25). However, they have a high potential for radically new high-tech innovations (Mas-Machuca et al., 2014).

Indicators for artificial neural networks	*Data from different time points of several historical cases required*
Predecessor's growth slows down, Standards exist, Sentiment of internet forums, Number of articles in the popular media, Bibliometric data, Development effort and capabilities, Forward citations of patents, Novelty of the patent, Patent growth speed, Quantity of patents, Science-intensity, Scope and coverage of patents, Abnormal stock returns, Purchasing power, Number of product announcements, Number of trade fair presentations, New firm entry, New incumbent firm entry, Sentiment of the popular media, Number of online reviews, Number of product reviews in the media, Sentiment of online reviews, Product performance increases, Product price decreases, and Production capacity increases	

Figure 25: Indicators for the artificial neural networks

5.2 Second stage

The first stage already provides decent reliability in most cases. However, the methods have limitations or disadvantages because of their methods applied. Therefore, the second stage in the forecasting approach can be used to improve the initial method by using a hybrid approach to overcome the limitations. In the following sections, it will be explained how methods can be enriched for better reliability.

5.2.1 Enhanced judgemental techniques

The judgemental techniques assumptions-based modelling and Delphi method can be enhanced by combining them with time series & regression models or artificial neural networks.

Enhancing with time series & regression models

A major downside of the techniques assumptions-based modelling and the Delphi method is the missing comparison to historical cases. By combining the techniques with a time series analysis, the variation of the judgemental indicators can be analysed over time. Instead of rating the indicators only according to the current scenario, indicators will be rated at various time points throughout history, resulting in a time series of independent variables (see Figure 26). The rating of the indicators would happen according to the initial method's design. A data analyst could then calculate the regression model based on the time series of indicators.

Indicators for the assumptions-based modelling & Delphi method
Enhanced by time series & regression models

Data from historical time points required

Frequency of product changes decreases, Dominant category selected, Number of product categories decreases, Complementary products and services available, Bandwagon effect, Network externalities, Associations, coalitions, or groups formed, Laws and Regulation, Identified as a megatrend, Certain customer requirements, Certain product specifications, Availability of materials, suppliers, etc, and Quality of patents

Recommended non-judgemental indicators for missing categories

New firm entry, New incumbent firm entry, Number of product announcements. Number of trade fair presentations, Number of online reviews, Number of product reviews in the media, Sentiment of online reviews, Product performance increases, Sentiment of the popular media, Product price decreases, Abnormal stock returns, and Purchasing power

Figure 26: Indicators for the judgemental techniques enhanced by time series & regression models

The disadvantage of the judgemental methods, lacking a historical time series comparison, is turned into an advantage while still basing the forecast on judgemental indicators. However, the enhancement also introduces naiveness into the model. A standardized behaviour is expected from the diffusion pattern according to the regression models. The analysis for the two enhanced judgemental techniques would be based upon the data shown in the overview box.

After the validation, it was found that the judgemental indicators miss out on five categories required for a holistic assessment of the situation (see Section 6.1.2). It is recommended to add the non-judgemental indicators of these categories for a complete assessment. No expert is required to assess the indicators. Information is fairly easily available due to the nature of the indicators.

To avoid naiveness, one might consider deploying an artificial neural network upon the judgemental indicators. The approach will be discussed in the next section.

Enhancing with artificial neural networks

Another approach to increase the reliability and depth of the analysis for the judgemental techniques assumptions-based modelling and Delphi method is to enhance the methods by utilizing an artificial neural network. Judgemental indicators can then be analysed for patterns in historical cases after experts have rated the indicators.

However, the bias might still be high because experts assess many judgemental indicators for different time points and various historical cases (see Figure 27). Furthermore, more problems might shallow because each historical case requires experts knowledgeable in the case. This requirement would result in many different experts and high time consumption. Especially if the Delphi method is used to rate the indicators, time consumption might be too high for the achieved outcome due to multiple anonymous rating rounds.

After the validation, it was found that the judgemental indicators miss out on five categories required for a holistic assessment of the situation (see Section 6.1.2). It is recommended to add the non-judgemental indicators of these categories for a complete assessment. No expert is required to assess the indicators. Information is fairly easily available due to the nature of the indicators.

Indicators for the assumptions-based modelling & Delphi method
Enhanced by artificial neural networks

Data from different time points of several historical cases required

Frequency of product changes decreases, Dominant category selected, Number of product categories decreases, Complementary products and services available, Bandwagon effect, Network externalities, Associations, coalitions, or groups formed, Laws and Regulation, Identified as a megatrend, Certain customer requirements, Certain product specifications, Availability of materials, suppliers, etc, and Quality of patents

Recommended non-judgemental indicators for missing categories

New firm entry, New incumbent firm entry, Number of product announcements. Number of trade fair presentations, Number of online reviews, Number of product reviews in the media, Sentiment of online reviews, Product performance increases, Sentiment of the popular media, Product price decreases, Abnormal stock returns, and Purchasing power

Figure 27: Indicators for the judgemental techniques enhanced by artificial neural networks

5.2.2 Enhanced quantitative techniques

The quantitative techniques time series & regression models and artificial neural networks only use quantitative indicators in their analysis. This exclusion of judgemental data is a significant disadvantage because judgemental indicators might reveal a situation not assessed by quantitative indicators. The quantitative models can be enhanced in two ways by using assumptions-based modelling or the Delphi method. The approach for both methods will be discussed in the following sections.

Enhancing with assumptions-based modelling

A relatively easy way to include judgemental indicators in the quantitative techniques is using the assumptions-based modelling for both the artificial neural networks and time series & regression models. Compared to the later-described Delphi method approach, assumptions-based modelling is time-saving because multiple rating rounds are not required. Especially in artificial neural networks that require data from different historical timepoints and various historical cases, the time consumption for the data collection might be high. In such a case, the assumptions-based modelling is preferred if the bias prevention measures of the Delphi method are not necessary or too time-consuming for the desired outcome. Indicators that should be used for the enhanced time series & regression models and the artificial neural networks are shown in Figure 28 and Figure 29, respectively. The indicators do not differ per method. However, the required variety of historical cases is increased for artificial neural networks.

Indicators for the time series & regression models
Enhanced by assumptions-based modelling

Data from historical time points required

Frequency of product changes decreases, Dominant category selected, Number of product categories decreases, Complementary products and services available, Bandwagon effect, Network externalities, Associations, coalitions, or groups formed, Laws and Regulation, Identified as a megatrend, Certain customer requirements, Certain product specifications, Availability of materials, suppliers, etc, Quality of patents, Predecessor's growth slows down, Standards exist, Sentiment of internet forums, Number of articles in the popular media, Bibliometric data, Development effort and capabilities, Forward citations of patents, Novelty of the patent, Patent growth speed, Quantity of patents, Science-intensity, Scope and coverage of patents, Abnormal stock returns, Purchasing power, Number of product announcements, Number of trade fair presentations, New firm entry, New incumbent firm entry, Sentiment of the popular media, Number of online reviews, Number of product reviews in the media, Sentiment of online reviews, Product performance increases, Product price decreases, and Production capacity increases

Figure 28: Indicators for the time series & regression models enhanced by assumptions-based modelling

Indicators for the artificial neural networks
Enhanced by assumptions-based modelling

Data from different time points of several historical cases required

Frequency of product changes decreases, Dominant category selected, Number of product categories decreases, Complementary products and services available, Bandwagon effect, Network externalities, Associations, coalitions, or groups formed, Laws and Regulation, Identified as a megatrend, Certain customer requirements, Certain product specifications, Availability of materials, suppliers, etc, Quality of patents, Predecessor's growth slows down, Standards exist, Sentiment of internet forums, Number of articles in the popular media, Bibliometric data, Development effort and capabilities, Forward citations of patents, Novelty of the patent, Patent growth speed, Quantity of patents, Science-intensity, Scope and coverage of patents, Abnormal stock returns, Purchasing power, Number of product announcements, Number of trade fair presentations, New firm entry, New incumbent firm entry, Sentiment of the popular media, Number of online reviews, Number of product reviews in the media, Sentiment of online reviews, Product performance increases, Product price decreases, and Production capacity increases

Figure 29: Indicators for the artificial neural networks enhanced by assumptions-based modelling

Enhancing with the Delphi method

Bias prevention is the major advantage of the Delphi method over assumptions-based modelling. Although the Delphi method requires more time and commitment due to the multiple rating rounds, the extra effort compared to the assumptions-based modelling might be worth it if increased reliability is required for the forecast. Both the time series & regression models and artificial neural networks can be enhanced by including judgemental indicators (see Figure 30 and Figure 31, respectively).

Indicators for the time series & regression models
Enhanced by the Delphi method

Data from historical time points required

Frequency of product changes decreases, Dominant category selected, Number of product categories decreases, Complementary products and services available, Bandwagon effect, Network externalities, Associations, coalitions, or groups formed, Laws and Regulation, Identified as a megatrend, Certain customer requirements, Certain product specifications, Availability of materials, suppliers, etc, Quality of patents, Predecessor's growth slows down, Standards exist, Sentiment of internet forums, Number of articles in the popular media, Bibliometric data, Development effort and capabilities, Forward citations of patents, Novelty of the patent, Patent growth speed, Quantity of patents, Science-intensity, Scope and coverage of patents, Abnormal stock returns, Purchasing power, Number of product announcements, Number of trade fair presentations, New firm entry, New incumbent firm entry, Sentiment of the popular media, Number of online reviews, Number of product reviews in the media, Sentiment of online reviews, Product performance increases, Product price decreases, and Production capacity increases

Figure 30: Indicators for time series & regression models enhanced by the Delphi method

Indicators for the artificial neural networks *Enhanced by the Delphi method*	*Data from different time points of several historical cases required*
Frequency of product changes decreases, Dominant category selected, Number of product categories decreases, Complementary products and services available, Bandwagon effect, Network externalities, Associations, coalitions, or groups formed, Laws and Regulation, Identified as a megatrend, Certain customer requirements, Certain product specifications, Availability of materials, suppliers, etc, Quality of patents, Predecessor's growth slows down, Standards exist, Sentiment of internet forums, Number of articles in the popular media, Bibliometric data, Development effort and capabilities, Forward citations of patents, Novelty of the patent, Patent growth speed, Quantity of patents, Science-intensity, Scope and coverage of patents, Abnormal stock returns, Purchasing power, Number of product announcements, Number of trade fair presentations, New firm entry, New incumbent firm entry, Sentiment of the popular media, Number of online reviews, Number of product reviews in the media, Sentiment of online reviews, Product performance increases, Product price decreases, and Production capacity increases	

Figure 31: Indicators for artificial neural networks enhanced by the Delphi method

However, as mentioned before, one should pay attention to the increased effort needed for the enhanced artificial neural network method. Not only data from historical time points for the large number of quantitative and judgemental indicators is required but also from several historical cases.

5.3 Comparison between regular and enhanced forecasting techniques

The enhancements for the forecasting techniques are quite detailed, and an overview is necessary for a complete comparison. Hence, the regular and enhanced forecasting techniques will be compared with each other in Table 14. The criteria are similar to the original criteria used in Section 3.1.5 and evaluated based on the advantages and disadvantages in Section 5.1 and 5.2.

Reliability

The essential characteristic of a forecasting technique is the reliability. It is assumed that the enhanced methods have increased reliability over the standard methods (compare Cho, 2013). Methods have been combined so that the disadvantages of the primary method are overcome by a combination with a secondary method of another forecasting category. This combination of methods means that the reliability of each enhanced method is a notch higher than the original method depending on the selected secondary method. For example, the enhanced Delphi method has a high and very high reliability, for an enhancement with the time series & regression models and the artificial neural networks, respectively, compared to the initial medium reliability of the regular Delphi method.

Time consumption & ease of operation

However, the time consumption increases and the difficulty of operation for the enhanced judgemental methods as well. In detail, the time consumption of the enhanced judgemental methods increases because of the increased data required for historical cases and the extra steps to process the forecast. Additionally, the ease of operation decreases because the enhancements by the quantitative methods are more complex than the original judgemental techniques.

Concluding this, combining methods also means that more steps are required to collect data, prepare the forecasting technique, and execute the forecast. These additional steps increase the time consumption and the difficulty of the enhanced judgemental methods. For the enhanced quantitative techniques, the increased time consumption and difficulty are marginal compared to the regular method’s time expenditure and complexity. Adding judgemental indicators to the already complex quantitative analysis has only a small effect on the time consumption. Therefore, their rating has not increased.

Industry experts

All enhanced methods, as well as the regular judgemental methods, require a minimum of one industry expert due to the judgemental indicators integrated in all enhanced methods. Preferably, even more experts to receive a broad perspective on the judgemental indicators. The regular quantitative techniques do not require an industry expert as they only incorporate non-judgemental indicators in their original state. However, artificial neural networks require a data scientist to set up the method, train the model, and calculate the forecast.

Bias prevention

Due to the strong emphasis on judgemental indicators, the bias prevention for the enhanced Delphi method and enhanced assumptions-based modelling is not improved. Unlike the judgemental methods, the bias prevention of the enhanced time series & regression models and artificial neural networks is decreased if the methods are combined with assumptions-based modelling. The introduction of objective indicators influences the overall prevention of bias for the quantitative techniques negatively.

Bias prevention is less negatively influenced if the quantitative forecasting techniques are enhanced by the Delphi method. This is because the Delphi method provides a robust framework reducing bias systematically while simultaneously including judgemental indicators.

Required data

Moreover, the required amount of data is increased if a quantitative technique enhances a regular judgemental method. For example, in the case of time series & regression models enhancement, historical data points of the innovation in focus are required. The regular judgemental method did not require these historical data points. Suppose a user decides to enhance a technique by an artificial neural network, additionally to historical data points. In that case, a variety of historical cases are required to train the neural network and an increased variety of indicators. These implications of the required amount of data should be considered while deciding on a forecasting technique.

For the enhanced quantitative methods, the required amount of data increases only marginal by the judgemental indicators because most data come points from the quantitative indicators. Therefore, the rating in Table 14 is not increased.

Table 14: Comparison of normal and enhanced forecasting techniques

Criteria	**Delphi method**			**Assumption-based modelling**			**Analogous forecasting**	**Time series & regression models**			**Artificial neural networks**		
Forecasting technique	Normal	Enhanced by time series & regression models	Enhanced by artificial neural networks	Normal	Enhanced by time series & regression models	Enhanced by artificial neural networks	Normal	Normal	Enhanced by assumptions-based modelling	Enhanced by the Delphi method	Normal	Enhanced by assumptions-based modelling	Enhanced by the Delphi method
Reliability	medium	high	very high	low	medium	high	low	medium	medium to high	high	high	high to very high	very high
Ease of operation	medium	medium	low	high	medium	low	high	medium	medium	medium	low	low	low
Time consumption	medium	high	very high	low	high	very high	low	high	high	high	very high	very high	very high
Industry experts necessarily required	yes	yes	yes	yes	yes	yes	yes	no	yes	yes	no	yes	yes
Prevention from bias	medium	medium	medium	low	medium	medium	low	high	medium	high	high	medium	high
Variety of case studies required	no	no	high	no	no	high	high	no	no	no	very high	very high	very high
Variety of independent variables required	medium	medium	high	medium	medium	high	medium	medium	medium	medium	high	high	high
Historical data points per independent variable	no	yes	yes	no	yes	yes	no	yes	yes	yes	yes	yes	yes

To conclude Table 14, it can be observed that the reliability of a forecast increases if an enhanced technique is used that combines two different forecasting techniques. Especially the quantitative techniques as an add-on to the qualitative techniques have a decent impact on the technique's reliability. However, also qualitative methods have their edge. Especially the single methods without an enhancement are easy to use and can provide insights that do not have to follow a prescribed trend or formula like the quantitative techniques (see Section 3.1.1).

Moreover, the required data for the quantitative techniques or the hybrid techniques is drastically increased. This is because quantitative techniques can only work well if a large amount of data is on hand. However, extensive data amounts for quantitative techniques require more time and resources to gather, sort and clean the data.

Nevertheless, quantitative data has less influence on the bias than qualitative data. The qualitative methods are generally more open to bias because of the direct influence of the experts. Therefore, the quantitative methods are better protected from bias than the qualitative techniques. However, qualitative methods like the Delphi method try to keep the influence of bias as low as possible by using knowledge sharing and individual and iterative interview rounds.

Generally, not one forecast method can be recommended for every situation. While an enhanced quantitative method might be suitable in one situation, another requires a single qualitative technique. The selection of the forecasting method is highly case dependent. Therefore, the forecasting approach offers all 13 forecasting techniques and guides a user towards its recommended technique.

6 Validation

To validate the research in this master thesis, various measures have already been applied during the research according to the methodology described in Section 2.1.3. However, for the final validation, three main components are still missing: (i) Completeness of the indicators, (ii) Demo case studies, and (iii) Expert interviews. Therefore, these final validation steps will be completed in the following sections to prove if the research and findings are legitimate.

6.1 Completeness of the indicators

For the completeness check, the indicators will be categorized according to the 14 factors based upon the factors of Ortt and Kamp (compare Section 3.7). This check is based on the assumption that the 14 factors give a holistic picture of an environment around an innovation, an innovating firm, and the innovation itself (compare Section 2.1.3 and 3.7.1). Therefore, the framework by Ortt and Kamp can be used as a benchmark for the completeness of the indicators. First, the indicators before the final selection will be categorized. Afterwards, the indicators in the final list will be categorized. Additionally, the changes between both will be compared.

6.1.1 Before final selection

Observing indicators found in the literature or derived from the literature in Chapter 3 are summarized in Figure 32. These indicators have been categorized into 14 categories. The primary differentiation between building blocks and influencing indicators is shown in blue. The next level of detail in terms of categorization is shown in yellow. Indicators in these categories are measuring a somewhat similar notion or construct.

No indicator has been considered for the category accidents and events. This can be explained since accidents cannot or are usually not simple to predict. Given this explanation, a lack of indicators in the category accidents and events is not proof of incompleteness.

Only one indicator has been found for three categories (complementary products and services, natural, human, and financial resources, and social-cultural aspects). One could argue that one indicator is not sufficient and might be too arbitrary. However, the categories complementary products and services and natural, human, and financial resources are quite focused and not many more indicators can cover the construct. Therefore, it might be impossible to find other indicators in these two categories that apply to all kinds of radically new high-tech innovations. However, for specific use cases, more indicators could exist in these categories. Besides this general check for completeness of the indicators, a case-specific check will be done in validation interviews. For the validation interviews, green hydrogen has been selected as the innovation in focus. If more indicators are required in these categories for the prediction of green hydrogen will be analysed and discussed in Section 6.3.2.

For the third category, social-cultural aspects, the critique is valid. Socio-cultural aspects do play a role during the diffusion. If customers are willing to adopt a technology and what loose regulations exist in a society are a few questions that might be asked for the start of diffusion (compare Ortt & Kamp, forthcoming). However, socio-cultural aspects are usually relatively steady over a short timeframe.

Although socio-cultural aspects influence adoption rates, an incremental change in the socio-cultural aspects might be impossible to measure. Therefore, socio-cultural aspects can be seen as given and exogenous for the forecast. Therefore, a lack of indicators in this category will not be seen as an issue. The other categories are pretty complete and have from two to up to 11 indicators.

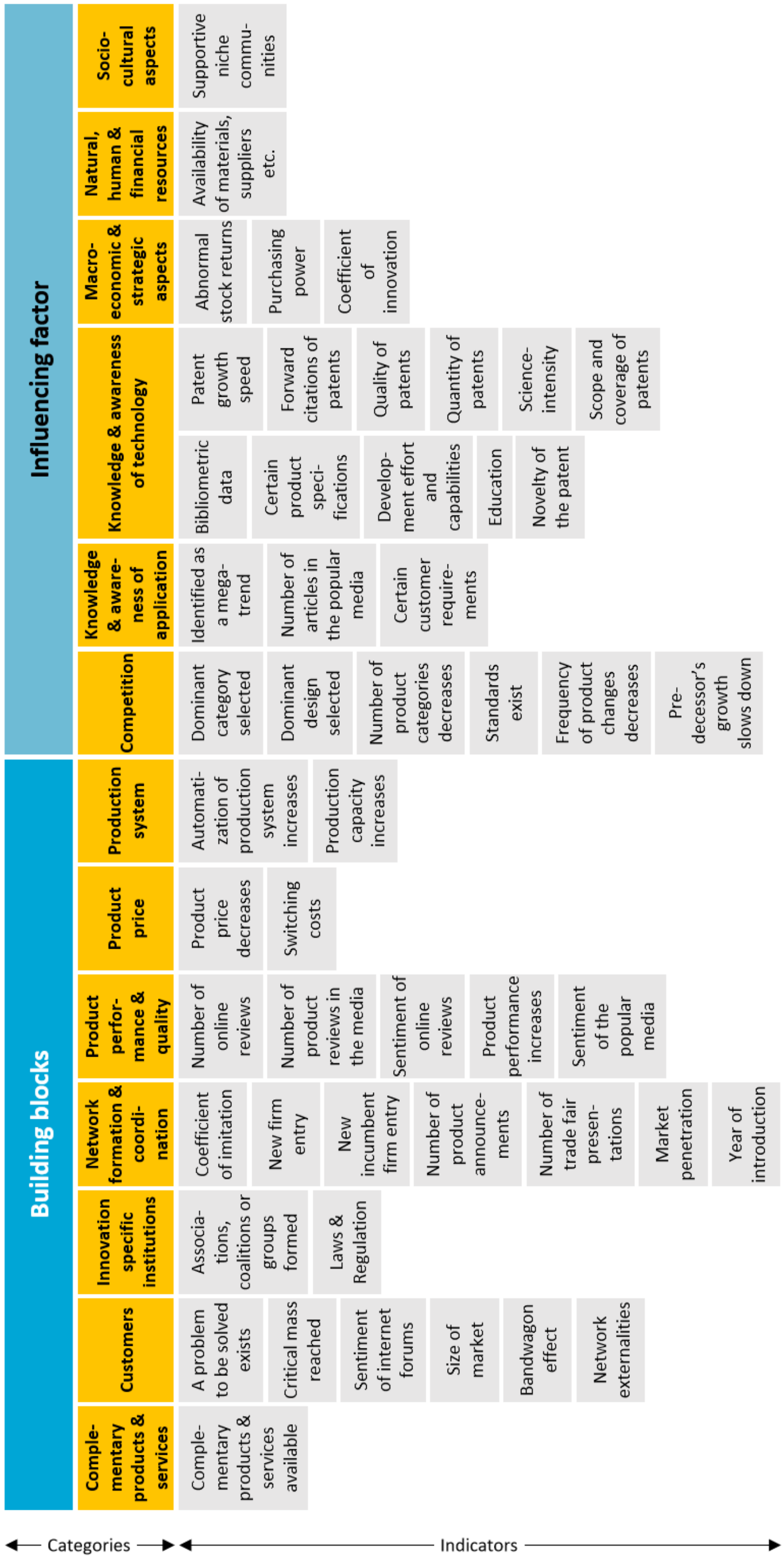


Figure 32: Classification of the observing indicators

6.1.2 After final selection

Neither the judgemental indicators nor the non-judgemental indicators have an indicator in the category of social-cultural aspects. The only indicator in the category, supportive niche communities, received a rating of 2,7 for predictiveness. Due to this low rating, the indicator has been excluded by the selection mechanism. Nevertheless, it has already been argued that socio-cultural indicators are seen as exogenous to the forecasting due to their long-term changes.

Judgemental indicators

The judgemental indicators miss out on a few building blocks (see Figure 33): network formation & coordination, product performance & quality, product price, production system, macro-economic & strategic aspects. The main reason behind this is that the indicators in these categories are mainly non-judgemental. This lack of indicators could be a problem if only judgemental indicators are used. However, if the combination of judgemental and non-judgemental indicators is used, the issue is resolved as suggested by the enhanced forecasting techniques. A specific focus of a user only on judgemental indicators but strictly excluding non-judgemental indicators is unlikely but also not impossible.

The later demo case A (see Section 6.2.1) will show that, for example, a startup could focus only on judgemental indicators to leverage their network and reduce the costs. In such a situation, the user must be warned that the judgemental indicators miss out on five categories if non-judgemental indicators are excluded.

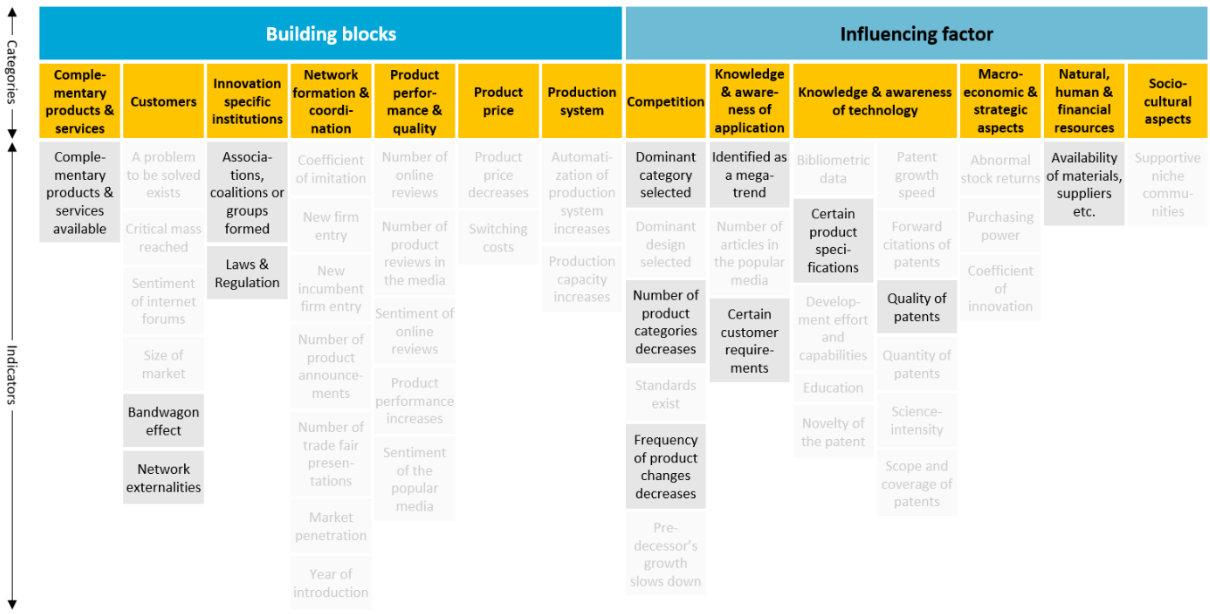


Figure 33: Selection of judgmental predictive indicators

Non-judgemental indicators

In comparison to that, non-judgemental indicators (see Figure 34) are especially strong in the categories of network formation & coordination, product performance & quality, and knowledge & awareness of technology, but miss indicators in the categories: complementary products & services, innovation specific institutions, and natural, human & financial resources. This lack of indicators is because these categories only have judgemental indicators. Although an enhanced forecasting technique could resolve this issue again, some users of the forecasting approach could prefer to only rely on non-judgemental indicators because of their objectivity. Therefore, it is recommended to add non-judgemental indicators for the categories complementary products & services, innovation specific institutions, and natural, human & financial resources. How a subsequent researcher can add more indicators for these three categories is explained in Section 7.3.1 as part of the future research.

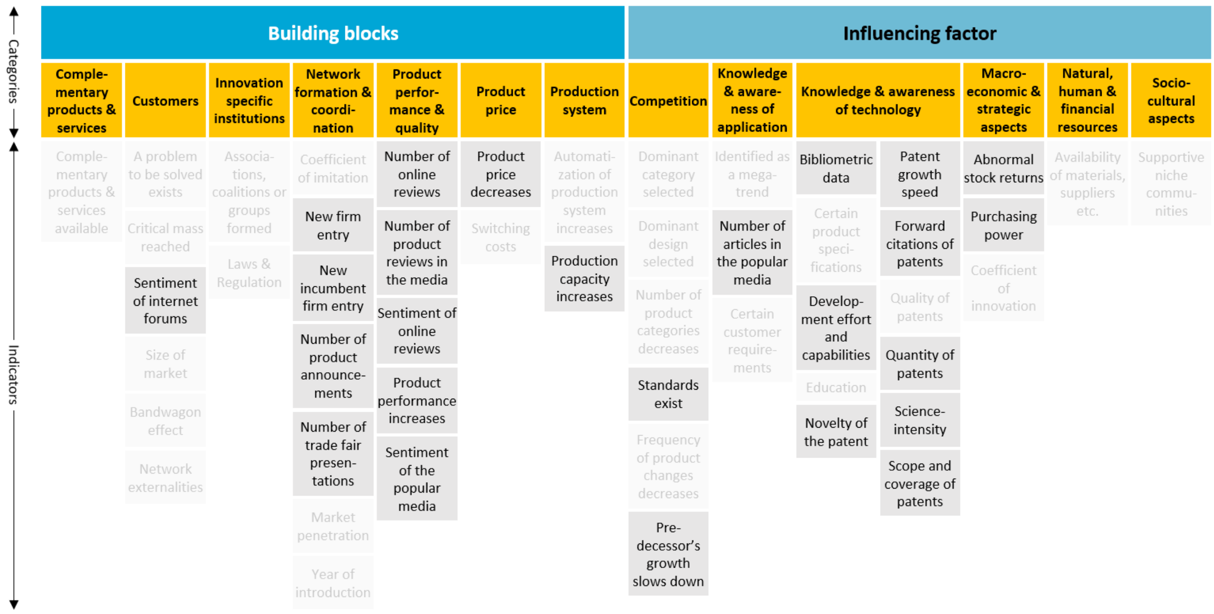


Figure 34: Selection of non-judgmental predictive indicators

Concluding this check for completeness, a few issues were found in specific categories. These issues will be further discussed in Section 7.3.1 regarding the limitations of the master thesis. In the following sections, the demo case studies will be presented.

6.2 Demo case studies

For the practical validation of the research, two demo case studies will be created to test the forecasting approach in an applied manner. Demo A is a small startup with limited resources in terms of employees, knowledge, and budget. In contrast, Demo B is a larger corporation with increased resource availability. These two contrasting companies will test the variability and flexibility of the forecasting approach.

The demo cases will be focused on green hydrogen. Green hydrogen is a radically new high-tech innovation currently in the adaptation phase, and its diffusion is anticipated (Ortt & Schmidt, forthcoming). Information is available in large quantities. Moreover, many companies would like to know when the diffusion of green hydrogen starts due to its immense impact on the energy, transportation, and metal industry. These characteristics make green hydrogen a perfect example for the demo case studies.

6.2.1 Demo A: Startup

The startup is a new entrant in the green hydrogen sector. Its main product is a consumer of green hydrogen, maybe related to the aircraft industry. Hence, the company would like to know when green hydrogen will be available in large quantities for the aircraft industry. According to this information, the startup can plan its product launch.

Assumptions

Due to its novelty, the startup is restricted in its human and financial resources. Additionally, the in-house knowledge about the market situation is limited too. However, the startup is well connected in its industry due to its membership in a university startup incubator. The incubator provides access to a diverse scientific and corporate network which provides the startup knowledge about recent developments.

Selection of the forecasting technique

The startup believes in the uniqueness of green hydrogen compared to other innovations. Hence, it will use an approach not based on historical data. Furthermore, the startup would like to decrease the bias and make use of its extensive network. Therefore, according to the forecasting approach, the forecasting technique Delphi method is recommended.

Because of the financial restriction, the startup refrains from using an enhanced method. The Delphi method could be improved by implementing a hybrid approach with the time series models or artificial neural networks. However, the time expenditure is immensely increased, and the startup does not employ a data scientist required to set up the method. Therefore, no enhancement is used. An overview of which path has been taken in the forecasting approach is shown in Figure 35.

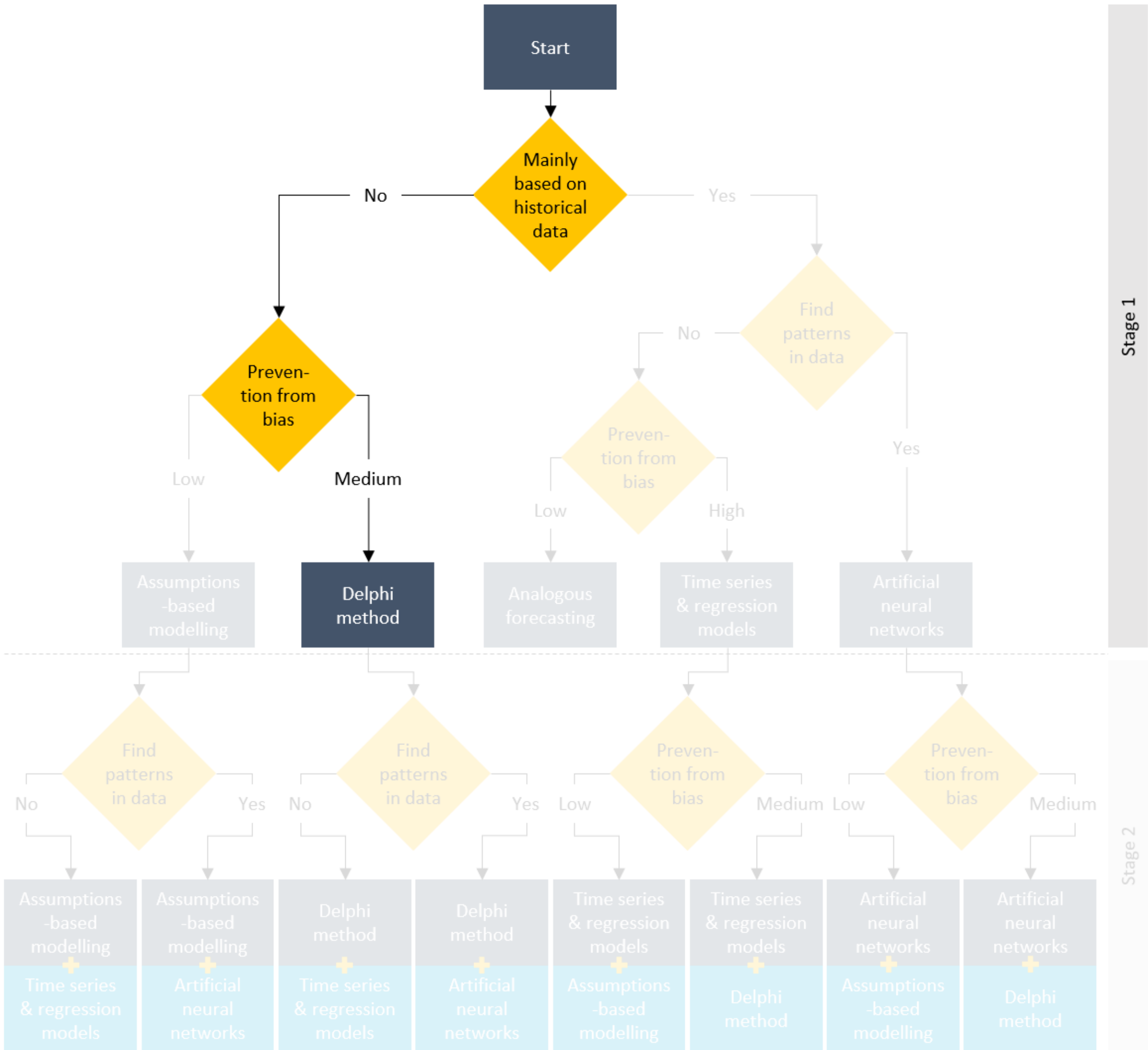


Figure 35: Path in the forecasting approach for Demo A

Selected method: Normal Delphi method

Along with the Delphi method are coming the indicators shown in Figure 36. The startup can leverage its local network in the incubator to review the indicators. Various rounds are required by the Delphi method, which could be organized in individual workshops for the respondents. In between the workshops, the information from other respondents can be shared to reduce the information bias.

The validation in the previous section has shown that non-judgemental indicators out of five categories are recommended to achieve a holistic assessment of the situation with the judgemental forecasting techniques. However, due to their tight budget, the startup refrains from adding these indicators initially and will reconsider this situation after the expert interviews.

Indicators for Demo A	*No historical cases required*
Frequency of product changes decreases, Dominant category selected, Number of product categories decreases, Complementary products and services available, Bandwagon effect, Network externalities, Associations, coalitions, or groups formed, Laws and Regulation, Identified as a megatrend, Certain customer requirements, Certain product specifications, Availability of materials, suppliers, etc, and Quality of patents	

Figure 36: Indicators for Demo A

The Delphi method prospects average reliability. To increase the reliability of the judgemental indicators, bias prevention measures are used. The time consumption and difficulty of the method are medium too. An enhancement of the method by a time series model or an artificial neural network would have increased the time consumption drastically due to more required data points.

In the following section, demo case B will be described. The company, in this case, is significantly larger, giving the company different opportunities according to the forecasting approach.

6.2.2 Demo B: Large corporation

The large corporation is home in the energy sector. While their previous business model relies on nuclear energy and coal, the climate goals enforce a change in the business model. Hence, renewable energies are getting more critical for the large corporation. Green hydrogen is required to fully reap the effects of renewable energies (Ortt & Schmidt, forthcoming). Therefore, the company would like to know when green hydrogen will diffuse on a large scale.

Assumptions

The large energy company is financially backed well. Additionally, the corporation operates globally and has thousands of employees in the operations, as well as the research and innovation department. Knowledge is available internally through reports and experts in their field. The company stays in fierce competition with other energy corporations. Unlike the startup, their network only exists internally. The external network is limited due to the intense competition between the companies in the energy sector.

Moreover, the reliability of the forecast is essential for the large corporation. Many projects are scheduled according to the timepoint of diffusion calculated by the forecasting technique. Therefore, a reliable technique is required to decrease the risk of being too late or early in the market.

Selection of the forecasting technique

Due to resource availability, the large corporation would like to use an approach emphasizing historical cases. Many employees can contribute towards gathering data from historical cases at different time points. The time and resources restriction from the startup does not exist. Additionally, the large corporation would like to use a technology leveraging pattern recognition. The company's ICT department has experience with artificial neural networks from previous projects. The company would like to use this knowledge to find the time point of large-scale diffusion of green hydrogen. Therefore, artificial neural networks seem to be the correct forecasting technique for the company.

To further increase the reliability, the company chooses to enhance the artificial neural networks by judgemental data. Employees of the company can be used as experts to rate the judgemental indicators. Nevertheless, the Delphi method with its bias reduction is not required. Internal employees have similar knowledge, and knowledge sharing through the Delphi method is not necessary. The other option, assumptions-based modelling, is chosen. An overview of which path has been taken in the forecasting approach is shown in Figure 37.

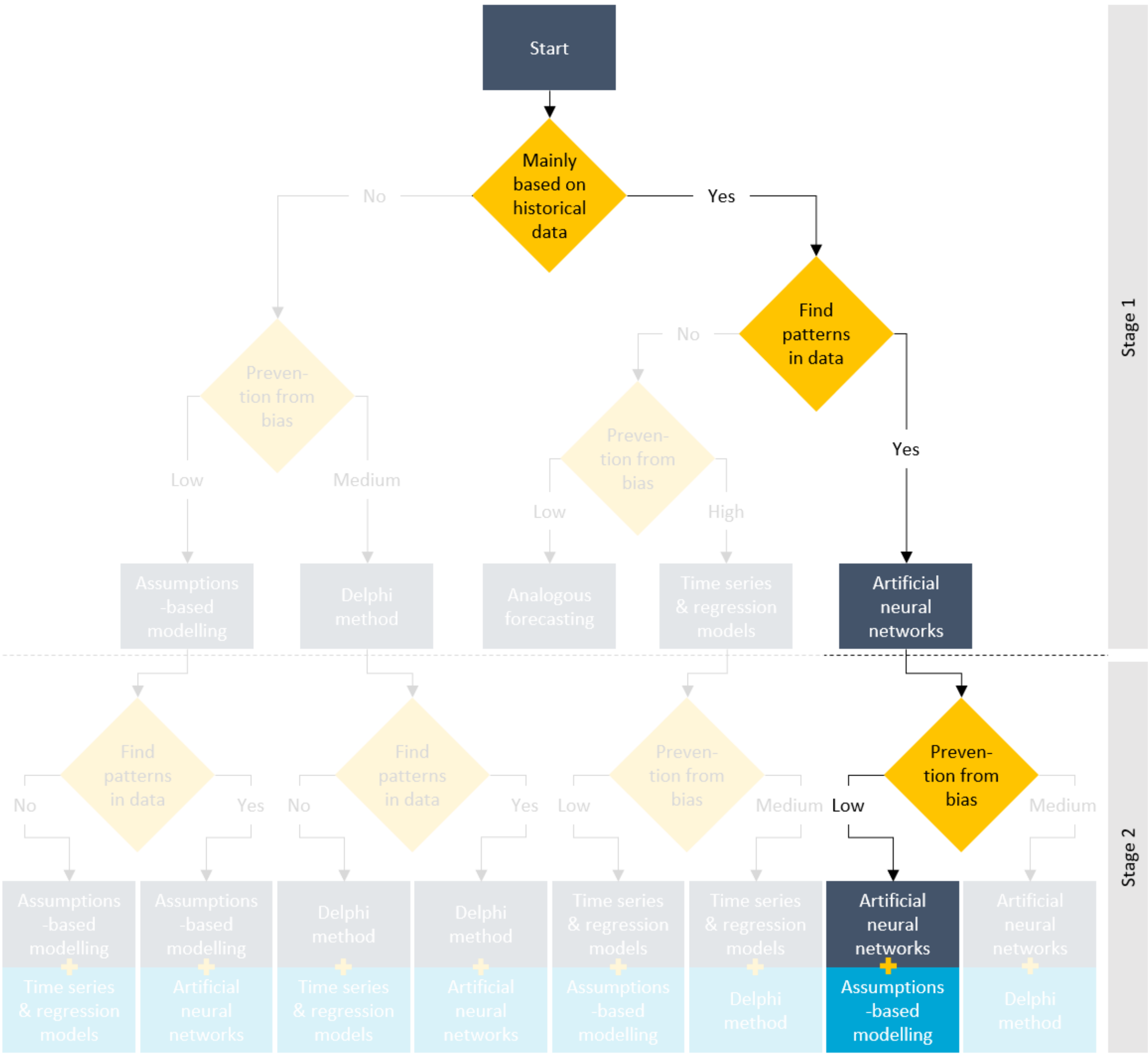


Figure 37: Path in the forecasting approach for Demo B

Selected method: Artificial neural network enhanced by assumptions-based modelling

Indicators shown in Figure 38 can be used for the artificial neural network enhanced by assumptions-based modelling. Because of the selected approach, non-judgemental and judgemental data from historical time points, as well as from other historical cases besides green hydrogen, are required.

Indicators for Demo B

Data from different time points of several historical cases required

Frequency of product changes decreases, Dominant category selected, Number of product categories decreases, Complementary products and services available, Bandwagon effect, Network externalities, Associations, coalitions, or groups formed, Laws and Regulation, Identified as a megatrend, Certain customer requirements, Certain product specifications, Availability of materials, suppliers, etc, Quality of patents, Predecessor's growth slows down, Standards exist, Sentiment of internet forums, Number of articles in the popular media, Bibliometric data, Development effort and capabilities, Forward citations of patents, Novelty of the patent, Patent growth speed, Quantity of patents, Science-intensity, Scope and coverage of patents, Abnormal stock returns, Purchasing power, Number of product announcements, Number of trade fair presentations, New firm entry, New incumbent firm entry, Sentiment of the popular media, Number of online reviews, Number of product reviews in the media, Sentiment of online reviews, Product performance increases, Product price decreases, and Production capacity increases

Figure 38: Indicators for Demo B

6.2.3 Conclusions from the demo cases

The demo companies have been selected to present two very different firms. Although this quite limited application, a forecasting approach could have been found to fit the companies' characteristics and expectations for both demo case studies.

Due to the limited resources but extensive expert network for Demo A, a judgemental forecasting technique with medium reliability has been recommended according to the forecasting approach. Contrasting this, Demo B settled with a complex quantitative method enhanced by judgmental indicators. This method is far more time consuming but achieves better results and fits well to the firm's attributes.

It has already been mentioned that this validation is somewhat limited and might have a hindsight bias. The expert interviews in the next section should improve the validation through an external perspective. Moreover, a more advanced validation method will be recommended in Section 7.3.5.

6.3 Validation interviews

Besides the demo cases, I undertook four interviews to present the findings to external researchers and employees, validate the work, and discuss criticism about the research and findings. Similarly like the demo cases, the interviews were focused on the green hydrogen industry. Each interview took about 40 to 45 minutes, and the core findings of the research have been discussed: practical relevance of the research, forecasting approach, indicators, criteria, and general feedback.

A structured interview guide of closed and open questions has been used to validate the findings. The structured interview guide has the advantage of higher comparability between the interview candidates than a semi-structured or open interview guide. The combination of different kinds of questions allowed me to strictly validate the research by using closed questions and collecting the candidates' opinions and reflections by using open questions. For the topics indicators and criteria, I asked the candidates to share their own indicators or criteria before showing them my work (see Figure 39). This way, the candidates answered the questions unbiased and afterwards reflected on my indicators and criteria. The interview guide has been piloted with a fellow MOT student beforehand, and minor changes have been made to the guide to improve the interview flow.

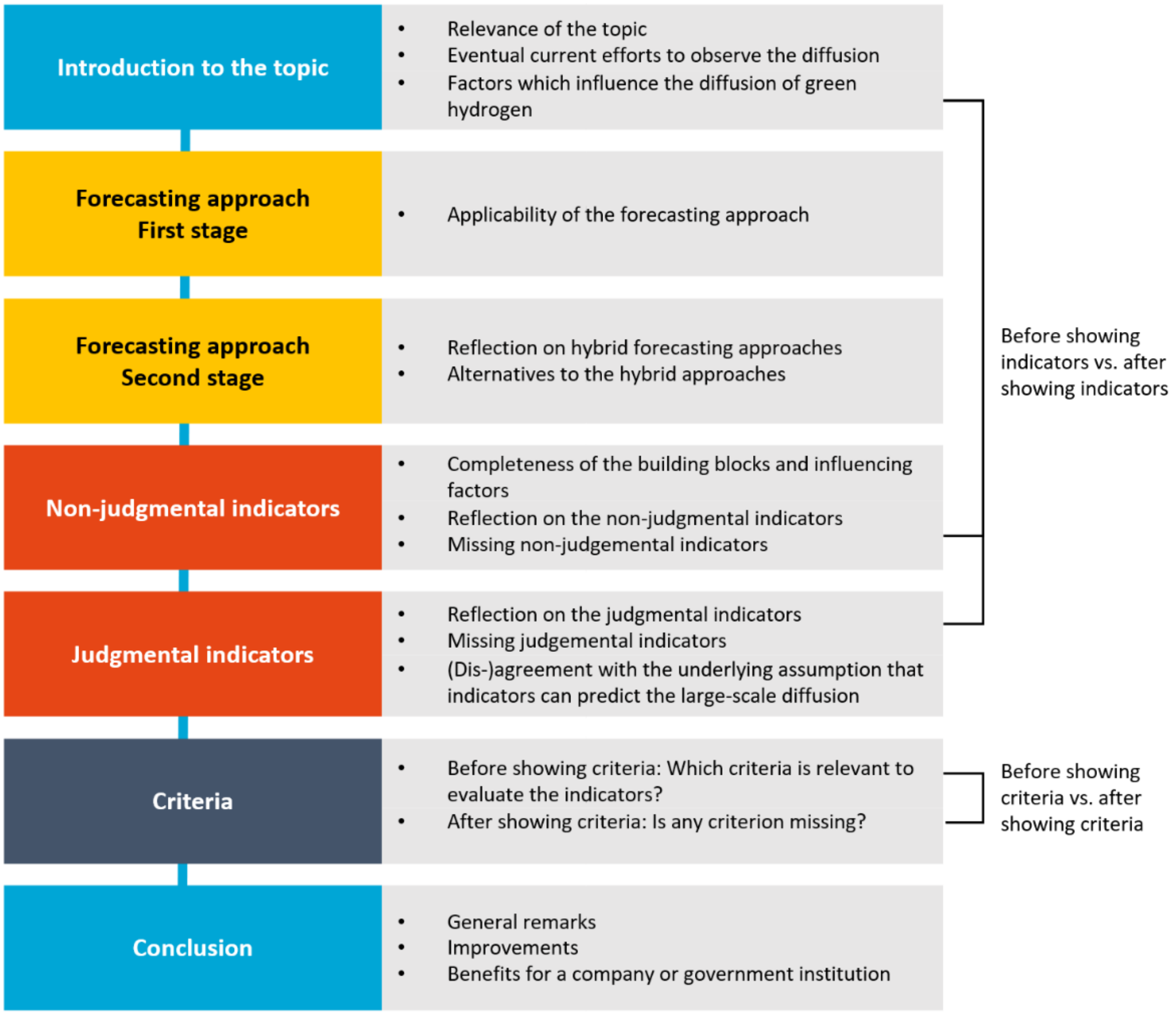


Figure 39: Structure of the interview guide

The background of each interview candidate can be seen in Table 15. During the interview with candidate A, only a limited number of questions have been asked due to the candidate's strong focus on the technical perspective of green hydrogen. Therefore, the interview's main focus with candidate A lay on understanding factors and barriers for the diffusion of green hydrogen.

Table 15: Background and expertise of the experts for the validation interviews

#	Job description	Expertise	Duration of work experience	Highest degree	Connection to hydrogen
A	Part-time professor at TU Delft, Netherlands	Technical perspective on future energy systems, entrepreneurship, renewable energy	At least 37 years in various roles as a researcher and entrepreneur	PhD in Physics from Utrecht University	In the candidate's work regarding full energy systems
B	Researcher at DNV, Netherlands	Power flexibility, smart grids, commercial-ization, research & development	At least 20 years in various roles and companies	MBA, TSM Business School MSc Chemical Engineering, University of Twente	In the candidate's work regarding power flexibility hydrogen plays a crucial role as an energy carrier
C	Manager Sales Development at Essent, Netherlands	Energy transition, infrastructure systems, new business development, business strategy	At least 12 years in the energy sector in various roles and companies	MSc Chemical Engineering, TU Delft	In the candidate's work regarding commercializing infrastructure systems
D	Researcher at the Kennisinstituut voor Mobiliteitsbeleid, Netherlands	Sustainable transport, energy carriers	At least 26 years in various roles and companies	Drs. Physics, Utrecht University	In the candidate's work regarding sustainable means of transport hydrogen works as an energy carrier

The results of the interviews will be discussed in the following paragraphs. In addition, a summary of each interview can be found in Appendix F.

6.3.1 Practical relevance

All interviewees were interested in the research objective and saw the practical relevance (Candidate A, 2021; Candidate B, 2021; Candidate C, 2021; Candidate D, 2021). Most candidates confirmed that knowing the time point of large-scale diffusion helps a company or researcher. Candidate C emphasised the possibility of investing in the right moment if the time point of diffusion is known. However, candidate B criticized that in a market where everybody would know the time point of diffusion of a technology, investments would be postponed and research delayed. This is a valid criticism. However, forecasts will differ depending on the underlying data and the forecasting technique used to calculate the forecast. Especially judgemental data will influence the forecast drastically, leading to different results.

Compared to the other candidates, candidate D (2021) is not interested in the time point of diffusion. Instead, the candidate's focus lies on the influential factors that lead to diffusion and the questions of which factor triggered the diffusion. This different interest can be explained due to the candidate's role as a researcher for a government institution. Throughout the interview, the candidate emphasized the importance of government subsidies as a necessity to create a market for green hydrogen. As a researcher for a government institution, the candidate is interested in the most influential factors and if the government can support in providing these factors or altering the factors to improve the diffusion speed.

Currently, various companies or institutions are observing the diffusion of green hydrogen in a rudimentary manner (Candidate B, 2021; Candidate C, 2021; Candidate D, 2021). However, a prediction based on the observations is hardly made.

Forecasting approach

Three candidates (Candidate B, 2021; Candidate C, 2021; Candidate D, 2021) found the forecasting approach applicable to green hydrogen (this part of the interview has not been done with candidate A). Especially the combination of judgemental and quantitative methods by an enhanced forecasting technique has been seen as a good addition to the original forecasting techniques. Candidate C argued that from their professional experience, judgemental data besides quantitative data has always been valued highly. Any candidate did not know an alternative method to overcome the disadvantages of the forecasting techniques.

Additionally, candidate B (2021) added that beginning with a quantitative analysis and subsequently adding a judgemental analysis is usually a good and easier start than starting the other way round. According to the candidate, the judgemental analysis is required due to its capability of predicting revolutions and breaks in trends, unlike the quantitative methods. Moreover, the candidate also criticized that quantitative techniques are usually naïve and reproduce a fixed pattern based on their mathematical description. This criticism further emphasizes the importance of judgemental methods and indicators.

In contrast, candidate D (2021) pointed out the bias introduced by the judgemental methods and the importance of covering the whole value chain of green hydrogen. However, the value chain coverage will be ensured through the indicators that are supposed to cover the entire environment around an innovation (see Section 6.1). This interpretation of the remark is further solidified because of the candidate's limited recommendations for other indicators. In the next section, the completeness of the indicators according to the interviewees will be discussed in more detail.

6.3.2 Indicators

Before showing the indicators

Before revealing the indicators, I asked the candidates about relevant factors for the diffusion of green hydrogen. Candidates A, B, and C (2021; 2021; 2021) emphasized capital expenditure (CAPEX costs) as the most important indicator for green hydrogen. Electrolysers for green hydrogen hardly run full time but only when peaks in the electric grid exist. Therefore, instead of lowering the operational expenditures (OPEX costs) driven by efficiency, the initial investment to build and set up the electrolyser is critical according to candidates A, B, and C.

In contrast, candidate D (2021) emphasized the efficiency factor and the projected efficiency factor for green hydrogen as the most crucial driver. This difference in argumentation of the candidates might be explained due to the specific background of candidate D in the hydrogen for mobility field. Hydrogen in the mobility sector is required in large quantities, demanding higher operating times, and therefore lower OPEX costs.

With candidate A I had a very extensive discussion about the required indicators to predict the diffusion of green hydrogen. The already mentioned CAPEX costs and electricity costs have been mentioned as the most dominant driver. Besides these two factors, the candidate (2021) mentioned:

1. Availability of solar, wind, and geothermal energy
2. Cost competitiveness compared to other alternatives in the market
3. Physical infrastructure
4. Policies for the CO2 emission price
5. Ease of use in the mobility sector
6. Production capacity

Comparing this to the indicators developed for the forecasting approach, it can be seen that not all factors are available in the forecasting approach. For example, the indicator *Product price* does not distinguish between CAPEX and OPEX costs. This crucial differentiation has not been made. Instead, the availability of solar, wind, and geothermal energy can be summarized under the more general indicator *Availability of material, supplier, etc*. Policies are summarized under the indicator *Laws & Regulation*. Production capacity and the concept of mass production leading to lower CAPEX costs are condensed under the indicator *Production capacity increases*. While the physical infrastructure might still be categorized into the indicator *Complementary products & services available*, no indicator represents the ease of use or cost competitiveness compared to alternatives.

At the end of the interview, the candidate questioned whether all these factors could be combined into “one innovation indicator” (Candidate A, 2021). The candidate sees the development around green hydrogen as a system and therefore recommends an approach in which green hydrogen is seen as a system and not as a separate technology. Seeing green hydrogen and other innovations with a system view is valid and also from my side recommended. However, the interviewee has not seen the overview showing the variety of indicators covering the environment or system around an innovation due to time constraints. Therefore, according to my understanding, the comment is based upon a misunderstanding. The forecasting approach uses a system approach to observe the innovation and its environment.

Generally, the importance of the comparison to other alternatives of green hydrogen has been stressed by all candidates (Candidate A, 2021; Candidate B, 2021; Candidate C, 2021; Candidate D, 2021). According to the candidates, green hydrogen is always seen in comparison to other energy carriers. Therefore, even if green hydrogen performs well in the indicators, green hydrogen will not diffuse on a large scale if a better performing alternative exists. Therefore, this comparison is a crucial missing component in the forecasting approach for the application on green hydrogen.

After showing the indicators and 13 categories

After this initial explorative question, I showed the 13 categories used to cluster the indicators and the indicators themselves in a stepwise approach to candidates B, C, and D. Besides an indicator measuring the competitiveness compared to the alternatives, candidate B (2021) mentioned a hype-cycle-similar behaviour for the judgemental indicators (compare Section 3.5.1). Although the candidate has not further detailed the hype-cycle-similar behaviour, careful attention should be paid to reduce the bias via trends on the judgemental indicators in subsequent research.

Candidate C (2021) recommended adding an indicator measuring the sustainability impact of green hydrogen. Green hydrogen is usually seen as the most sustainable energy carrier concerning the earlier mentioned comparison of alternative energy carriers. Such an indicator would work well if different energy carriers would be compared, and the assumption is made that the best energy carrier (measured according to different criteria or indicators) diffuses first. However, if the innovations are seen individually, the sustainability impact has no direct influence on the time of large-scale diffusion. The relation between sustainable technology and diffusion is more complex than this early assumption. If no demand for sustainable solutions exists, a higher or lower sustainability impact will not influence the diffusion.

Besides of this, the candidate (Candidate C, 2021) emphasized the importance of the indicators *New incumbent firm entry*, *Standard exists*, and all indicators related to the *popular media* because of the candidate's experience. The candidate shared a story during the interview in which an incumbent firm joined later the market. However, as soon as the incumbent firm was in the market, urgency and importance were created. Additionally, standards would be crucial to ensure the compatibility of technologies between firms. Lastly, announcements in the popular media are a signal of a soon to happen large-scale diffusion, according to the candidate. If news would reach the mass media, the technology is about to leave the niche sector and enter the mass market soon.

Throughout the interview, Candidate D (2021) emphasized that governments need to create a market for green hydrogen. Otherwise, cheaper alternatives would have a higher market share. However, given the background of candidate D, an indicator for market creation was missing. Nevertheless, the candidate later stressed that *Laws & Regulation* is a vital indicator to predict the diffusion based on market creation. Additionally, the candidate added that ease of use is an essential indicator for customers. The more straightforward to use a new technology is, the more customers will adopt the new technology.

Lastly, candidate D (2021) would like to know which actor influences who. While this might be out of scope for the current research objective, the importance of these insights for the candidate is understandable. As mentioned before, the candidate's main interest lies in understanding which factors influence diffusion most. Knowing this, the candidate can provide the correct levers for market creation in the candidate's role as a researcher for a government institution.

Concluding the four validation interviews, the following indicators or extensions to the model were missing according to the interviewees:

- Dividing product price in CAPEX and OPEX
- Ease of use
- Competitiveness to other alternatives
- Sustainability impact
- Actor influence

While the first two indicators can be added straightaway to the list of indicators after processing them through the data selection funnel, the extensions competitiveness to other alternatives, sustainability impact and actor influence have to be seen more critical given the research objective of predicting the time point of large-scale diffusion for radically new high-tech innovations. The interviews have shown that the competitiveness of green hydrogen is one of the most important factors for large-scale diffusion. However, this might only apply to green hydrogen, likewise the sustainability impact. Moreover, the identification of the actor influence might be out of scope. Further research is required to investigate the effect of the competitiveness to other alternatives, the sustainability impact, and actor influence on the diffusion of radically new high-tech innovations and prediction of the same.

6.3.3 Criteria

Reflections regarding the criteria used to evaluate the indicators were somewhat limited. Candidate B (2021) emphasized the importance of the criterion *Simplicity*. Not only an indicator should be easy to use and understandable, but also the forecast should be transparent. Additionally, candidate B (2021) would like to know which indicator led to a specific forecast. This interest matches the attention of candidate D. Both interviewees would like to know which indicator has the most impact on the diffusion of an innovation.

Moreover, candidate D (2021) is concerned that with about 40 indicators overlapping between the indicators might be inevitable. Therefore, indicators should be evaluated according to their uniqueness in the measurement to avoid that more than one indicator measures the same construct. If more than one indicator measures the same construct, it could lead to an overweighing of that construct in a forecast. This evaluation should be part of future research.

Lastly, candidates C and D (2021; 2021) stressed the robustness of each indicator and the forecasting approach overall. Especially if investments decisions are made in a company based upon the forecast for large-scale diffusion (see above, Section Practical Relevance), high reliability of the forecasting approach is required. This criticism matches my understanding that the current validation is insufficient for a practical application of the forecasting approach. How the forecasting approach can be validated better and the reliability ensured will be further discussed in Section 7.3.

6.3.4 General feedback and improvements

Throughout the interview, candidate B (2021) was content with the forecasting approach and its indicators in general. The candidate generally agreed with the initial assumption that the indicators could predict the large-scale diffusion of a radically new high-tech innovation. However, the indicators need to be more specific to the technology and its context to apply it to green hydrogen. Green hydrogen needs to be seen separately per application to ensure a better forecast. Then, the forecast would be helpful to spark a discussion internally in the company (Candidate B, 2021).

An improvement suggested by the candidate is the combination of the forecasting approach with a modelling approach (Candidate B, 2021). Different scenarios of diffusion and development could be modelled and forecasted to provide insights for a variety of developments. For example, what could be possible then is a forecast in an optimistic, pessimistic, and neutral manner. This three-folded prediction would increase the value of the forecast for the internal discussion.

Also, candidate C (2021) was pleased with the work. The forecasting approach could be relevant for its company's strategy department. Improvements besides the ones mentioned above were not remarked. However, candidate C would expect a proper validation of the approach before being applicable in a company.

Likewise, also candidate D (2021) was asking for complete validation of the forecasting approach. The candidate sees the forecasting approach as a first step, but more work is required to make it practically useful for an institute or company. As the only candidate, candidate D, disagreed with the assumption that the indicators would predict the time point of large-scale diffusion. According to candidate D, large-scale diffusion and its time point of diffusion depend on the market alternatives. Therefore, the indicators alone would not be sufficient. An actual application of the forecasting approach would show insofar this statement is correct or not.

7 Conclusion & Discussion

I started this master thesis to create the first foundations in the new scientific field of forecasting the start of large-scale diffusion of radically new high-tech innovations. This chapter will conclude my findings for this research problem by answering the research questions, discussing the work, and recommending future actions. Finally, to bring back the aim of the research into the reader's mind, the box below will summarize the research objective.

Research objective

Various models describe how the diffusion curve looks like, and much work has been done to predict the curve for new products in the market. However, research to predict the upcoming start of large-scale diffusion is currently scarce. Companies, researchers, and government institutions can benefit from knowing the start of large-scale diffusion in various ways. The forecast creates transparency, gives insights about influential factors, and serves as crucial information for investment decisions. Therefore, the objective of the master thesis is to develop a forecasting approach that can predict the upcoming start of large-scale diffusion.

7.1 Sub research questions

This section will answer the eight sub research questions (compare Figure 40) according to the previous chapters' findings. Subsequently, the main research question will be answered in the next section combining all sub research questions.

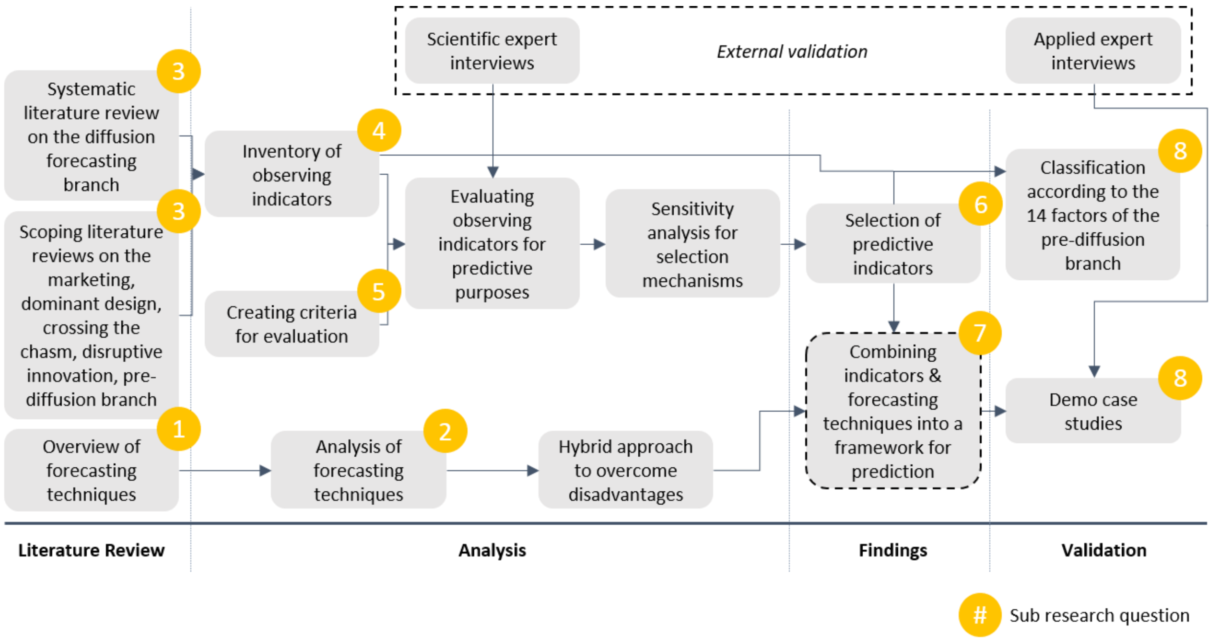


Figure 40: Recap research framework

SRQ1: Which forecasting techniques can predict the start of large-scale diffusion?

The literature reviews in Section 3.1 has shown that four categories of forecasting techniques exist: (i) Judgemental techniques, (ii) Time series & regression models, (iii) Consumer research techniques, and

(iv) Machine learning techniques. Out of these four categories, three categories can be used to predict the start of large-scale diffusion. Consumer research techniques cannot forecast large-scale diffusion due to their strong emphasis on consumer data. Consumers are only one of the 13 categories which measure the entire environment during the pre-diffusion phase. However, consumer research techniques, such as focus groups, can be used to gather data for consumer-related indicators, like the indicator *Certain customer requirements*.

The other forecasting categories (i), (ii), and (iv) can predict the large-scale diffusion as they can incorporate a broad range of judgmental and non-judgemental indicators from different categories depending on the method. In detail, the following methods were found to be relevant for the prediction:

- Assumptions-based modelling
- Delphi method
- Analogous forecasting
- Time series & regression models
    - Cox regression
    - Gompertz regression
    - Logistic regression
- Artificial neural networks

Additionally, hybrid approaches were developed, which overcome the disadvantages of the single approach. However, analogous forecasting is excluded from the hybrid approaches due to its unique characteristics compared to the other methods. Analogous forecasting is an expert-centred method for which an expert matches the innovation in focus with a historical innovation based upon similar innovation characteristics and its environment. Then, the matching historical innovation is used to predict the timepoint of diffusion. Therefore, the following hybrid approaches were found:

- Assumptions-based modelling enhanced by time series & regression models
- Assumptions-based modelling enhanced by artificial neural networks
- Delphi method enhanced by time series & regression models
- Delphi method enhanced by artificial neural networks
- Time series & regression models enhanced by assumptions-based modelling
- Time series & regression models enhanced by the Delphi method
- Artificial neural networks enhanced by assumptions-based modelling
- Artificial neural networks enhanced by the Delphi method

In total, 13 forecasting techniques can predict the large-scale diffusion of a radically new high-tech innovation. The number increases even further if the collection of time series & regression models is split into its three underlying regression models: Cox, Logistic, and Gompertz regression.

SRQ2: What characteristics does each forecasting technique have?

The characteristics of each forecasting technique have been described in detail in Section 3.1. Their advantages and disadvantages were explained in Sections 5.1 and 5.2. These characteristics were used to develop the already-mentioned hybrid approaches.

In conclusion, the characteristics shown in Table 14 were found for each forecasting technique and their enhanced hybrid approach. Generally, the reliability increases if an enhanced method is used. Contrasting this, the ease of operation decreases, and the time of operation increases because the complexity of the method expands.

The purely judgemental methods are the most effortless techniques and do not require data from historical timepoints. However, they require the involvement of industry experts, as their name suggests. On the other hand, purely quantitative methods are more reliable and have the highest degree of bias prevention. However, these methods always require data from historical time points. This historical data can drastically increase time consumption. A more in-depth description of the comparison can be found in Section 5.3

SRQ3: Which perspectives are relevant to derive observing indicators of large-scale diffusion of radically new high-tech innovations?

Due to the novelty of the research objective, a new explorative approach was needed to find and derive indicators from mechanisms during the pre-diffusion phase. To use a systematic approach, a so-called data collection cube was developed (see Figure 5). The cube consists of three perspectives: (i) indicator sources, (ii) indicator classes, and (iii) indicator types. Each perspective spits into a nominal scale of each three items.

The indicators can be found and derived from three sources: scientific literature, expert interviews, and case studies. Scientific literature was the only source used in this master thesis. The expert interviews and case studies have been omitted for the exploration of the indicators because of the limited time for the master thesis and their limited insights compared to the scientific literature.

The other two perspectives were used to ensure that indicators from a broad field are explored. Therefore, the indicator classes categorized indicators depending on their focus in three classes: technology side, market side, and contextual. These three categories cover the entire value chain with the technology and market side indicators, as well as more situational mechanisms in the contextual class.

Lastly, it was also essential to explore quantitative, qualitative, and dichotomous indicators of different types. This distinction was required because the forecasting techniques require different types of indicators (see Table 13). By minding the three different types of indicators, it was ensured that sufficient indicators were available for each forecasting technique.

SRQ4: Which indicators can be used to observe the large-scale diffusion of radically new high-tech innovations?

50 indicators, which can observe the start of large-scale diffusion of radically new high-tech innovations, were found and derived from the perspectives described in the previous paragraph. These 50 indicators passed the first two steps of the data selection funnel (see Figure 7). They were found to measure constructs related to timeliness and reflect on changing dynamics of the innovation in focus, its innovating firm, and the environment.

An overview of the observing indicators can be seen in Table 12. The indicators observe a wide range of mechanisms as the clustering according to the 13 factors of the pre-diffusion branch has shown (see Figure 32). However, one category, accidents and events, has been excluded from this clustering as accidents and unexpected events can be predicted hardly. After that, it was required to reduce the observing indicators to the predictive indicators by filtering them using criteria. The criteria which have been used to select the most potential indicators are described in the next paragraph.

SRQ5: Which criteria can evaluate if an observing indicator can predict?

Six selection criteria have been developed that distinguish if the observing indicators can also predict the upcoming start of large-scale diffusion:

- *Prediction*
- *Timeliness of prediction*
- *Availability of data*
- *Cost of data*
- *Quantifiable and objectivity*
- *Empirical proof*

These criteria assess first and foremost if the indicators predict at all (*Prediction* and *Timeliness of prediction*). Moreover, other essential characteristics of the indicators have been evaluated, such as the availability of data and the related costs of data gathering. The data underlying the indicator are almost as important as the prediction itself. Without data or high costs, the indicator's value is not justified. Lastly, more scientific characteristics have been assessed with the criteria *Empirical proof* and *Quantifiable and Objectivity*. Both criteria are required to ensure high scientific quality, validity, and reliability.

The criteria have been applied as part of the final step in the data selection funnel (see Figure 7) to answer SRQ6. In the correlation analysis, it was found that six combinations of criteria were significantly correlated. However, in Section 7.3, it was argued why the correlations can be neglected for now due to low correlations or the prevailing importance of the criteria *Availability and Cost of data*. Nevertheless, more research would be required to explore if the correlations affected the selection of indicators negatively.

SRQ6: Which of the observing indicators can predict the large-scale diffusion of a radically new high-tech innovation?

Out of the 50 observing indicators, 38 indicators had a sufficient rating in the selection criteria to be declared predictive indicators. An overview of the predictive indicators can be found in Figure 17. An average rating of neutral over all selection criteria was required to be included in the final list.

A selection mechanism was required to calculate this overall value. Five different selection mechanisms have been developed to increase the robustness of the mechanisms and avoid an arbitrary selection of an indicator. The results of each selection mechanism have been compared in a sensitivity analysis. The sensitivity analysis showed somewhat similar results for all selection mechanisms, excluding similar indicators, but Version 5 followed the most logical line of reasoning (see Table 16).

Table 16: Comparison selection mechanisms

Selection mechanism	Difference
1	Pre-check criteria *Prediction* & *Timeliness of prediction*, summing the other criteria including *Timeliness of prediction*
2	Pre-check criteria *Prediction* & *Timeliness of prediction*, summing the other criteria
3	Pre-check criterion *Prediction*, summing the other criteria
4	Summing all criteria except *Prediction*, multiplying with the criterion *Prediction*
5	Pre-check criterion *Timeliness of prediction*, summing all other criteria except *Prediction*, multiplying with the criterion *Prediction*

To check the completeness of the indicators, the indicators have been categorized after the factors of the pre-diffusion branch. The framework by Ortt & Kamp (forthcoming) has 14 factors that assess the environment around an innovation, the innovating firm and the innovation itself. These factors have been used to categorize the indicators and check them for their completeness. The predictive indicators were quite complete. However, for three categories, only one indicator each was found. This issue could be explained logically due to the definition of the factors (see Section 6.1.1). In a subsequent step, the indicators were split into a set of judgemental and a set of non-judgmental indicators. This step was necessary as a preparation for the forecasting approach combining the indicators with the forecasting techniques.

SRQ7: How can these indicators be combined into a forecasting approach to predict the large-scale diffusion of radically new high-tech innovations?

The 38 indicators and 13 forecasting methods were combined into one forecasting approach (see Figure 20). A user will be guided towards a forecasting method given her or his situation. A decision tree facilitates this decision-making process. Each of the 13 forecasting methods offers a specific set of indicators fitting to the method. Recommended indicators have to be seen as an offering, not all indicators have to be used by a user. Due to the limited timeframe, combinations of indicators and relationships among them have not been studied. This investigation is part of the future research required to make the forecasting approach more practically usable (see Section 7.3). A more complete overview of the forecasting approach is given in the next section answering the main research question.

SRQ8: What are validation methods to confirm the research regarding its face validity?

For this desk research, strict validation measures were required during the research process to safeguard the quality. As described in the methodology, two quality gates were used to ensure the scientific rigour and practicality of the research. For the quality gates, interviews with two expert groups have been conducted. First, researchers were asked to assess the predictiveness of the indicators based on their experience and knowledge. The data collected in these interviews played a significant role while selecting the final indicators. For the second quality gate, the practicality of the research was in focus. Industry experts were asked to confirm or reject the findings.

Besides these two quality gates, a check for completeness after splitting the indicators into judgemental and non-judgemental indicators and two demo case studies have been performed. The check for completeness improved the forecasting approach as it was found that the judgemental indicators lack indicators in five crucial categories. A disclaimer has been added to the forecasting approach to compensate for this lack, and non-judgemental indicators from these five categories are also recommended.

The demo case studies have been performed on two contrasting fictional companies: a startup and a large corporation. Assumptions per company were described, and based on the assumptions, a forecasting technique was recommended. No problems were found during the application of the three validation methods. However, the methods do not represent a real validation of the forecasting approach. The demo case studies have been used instead of an actual application due to a limited timeframe. An actual application of the forecasting approach on an existing case is recommended as part of future research (see Section 7.3.5).

7.2 Main research question

In this section, the main research question will be answered. This answer concludes the research of this master thesis. Findings from all previous sub research questions are combined for answering the main research question.

How can researchers and companies predict the upcoming large-scale diffusion of a radically new high-tech innovation?

This explorative master thesis has the aim of answering a novel research objective. Much research is already available for diffusion forecasting. However, the knowledge of predicting the start of large-scale diffusion for radically new high-tech innovations is scarce. Therefore, a forecasting approach has been developed to start future research in a new field. An overview of the forecasting approach can be seen in Figure 41. The complete forecasting approach can be seen in Figure 20.

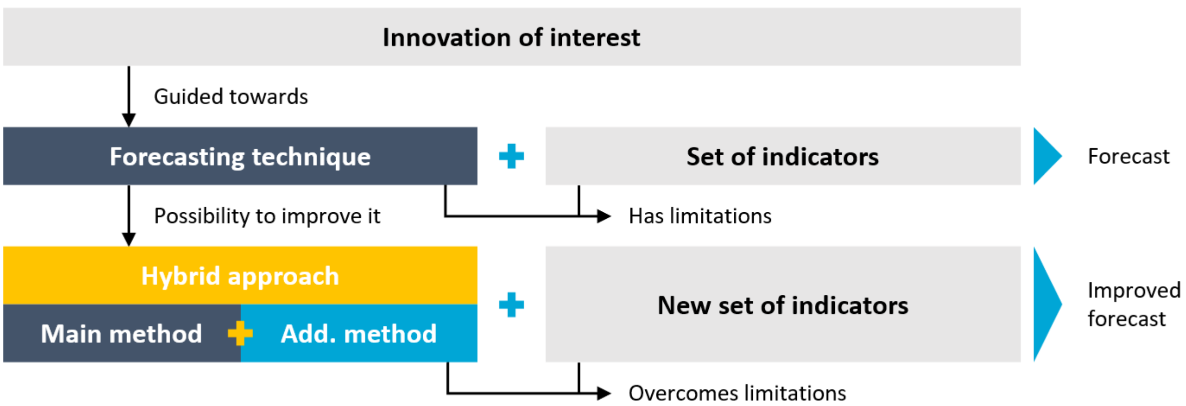


Figure 41: Overview of the forecasting approach

The forecasting approach consists of two stages. In the first stage, the primary forecasting method is chosen. If a user is confident with the recommended method and its reliability, it is unnecessary to go to stage two. However, the second stage improves the reliability by using a hybrid approach of the forecasting methods. Two forecasting methods are combined to rule out the disadvantages of the primary method. Alongside the forecasting techniques, indicators for each method are recommended (see Figure 21 to Figure 31). These indicators are an offer, and not all indicators have to be used (see Section 5.2).

This attempt of a forecasting approach summarizes the work done in this master thesis which hopefully inspires other researchers to take up the topic to improve it further. The topic is currently not complete, and limitations (see Section 7.3) hindering the application exist. Especially the missing understanding of how the indicators predict creates a challenge. Thus, the forecasting approach is in its current form not practically applicable. However, predicting the start of large-scale diffusion of radically new high-tech innovations is a highly relevant topic. More work by researchers is required to complete the main research question and turn this thesis's forecasting approach into a forecasting model for companies. Researchers and companies can benefit from more research in this field by better understanding the mechanisms during the pre-diffusion phase, recognizing mechanisms that lead to diffusion, and the actual prediction of the timepoint of large-scale diffusion.

7.3 Discussion, limitations of the research & future research

In this section, the research will be discussed and elaborated on the limitations of the research process. The discussion section will first look into the methodology in general and then focus on the main parts of the findings in more detail: criteria, indicators, forecasting approach, and validation. Per section recommendations for future research are advised to overcome the current limitations and improve the research.

7.3.1 Methodology

Much research has already been done for diffusion forecasting models after the start of diffusion (see Section 3.2). However, the pre-diffusion phase has not been explored sufficiently, focusing on predicting the start of large-scale diffusion (see Section 1.4). Hence, a new systematic methodology was required to explore scientific branches to find mechanisms influencing the diffusion, derive indicators, and combining the most potential indicators with relevant forecasting techniques.

Despite the successful work with the methodology, the application of the data collection cube and the validation methods can be criticized. Due to the limited time frame of the master thesis, a full exploration of the data and a thorough validation of the forecasting approach was not possible. A discussion with the mentors has shown that focusing on scientific literature branches is the best choice among the newly developed data collection cube (see Section 2.1.1). Although two other sources were part of the data collection cube (expert interviews and case studies), the assumption was made that scientific literature would cover the most mechanisms influencing the pre-diffusion phase.

Most literature reviews yielded sufficient results, and their findings were applicable to a varying extent (compare Figure 15). Especially the branches diffusion forecasting, macroenvironment, dominant design, and crossing the chasm generated a long list of potential indicators. The diffusion forecasting branch is somewhat unique in this list because the scientific field focuses on forecasting models to predict the diffusion curve after the start of large-scale diffusion. Therefore, variables could be directly extracted from the models. First, however, they had to be checked to comply with the indicator's criteria (see Figure 7).

The other three branches described mechanisms related to the start of diffusion, each from a different perspective. For example, the crossing the chasm branch was very customer centred. In comparison, the macroenvironment branch observed mechanisms around an innovating firm and innovation, and the dominant design branch especially emphasized the emergence of a leading product design. In conclusion, more than 30 indicators could have been derived from the literature branches' mechanisms and findings, and many of them found their way into the forecasting approach.

In contrast to this, the work with the disruptive innovation branch was less successful. Due to the branch's strict definition of disruptive innovations, not all findings applied to radically new high-tech innovations. Thus, only two indicators were derived from the disruptive innovation research. However, both indicators are used in the forecasting approach, making the findings and the literature review relevant for this research.

Additionally, the pre-diffusion branch has a particular position in the literature reviews. Not many indicators could have been derived because of the general and open definition of building blocks and influencing factors. However, the branch had a different task in this master thesis. At the beginning of the thesis, it was assumed that the pre-diffusion framework by Ortt & Kamp (forthcoming) covers the whole environment around an innovating firm, its innovation, and the innovation itself. The framework has also been used to check the indicators for their general completeness (see Section 6.1). In the six literature reviews, 50 indicators were found. Out of 50 indicators, 38 indicators were left after applying the selection mechanism.

In Section 6.1, a general check for completeness has been done by matching the indicators with the 14 categories of the framework by Ortt & Kamp. Most categories had sufficient indicators. However, this does not apply to all categories and all innovations. In general, more non-judgemental indicators are needed in the categories:

- Complementary products & services
- Innovation specific institutions
- Natural, human & financial resources

Two of the three categories are building blocks and, according to the framework, are highly relevant for the diffusion of an innovation. Therefore, the unavailability of non-judgemental indicators in these categories creates an issue, especially because users might decide to use only a quantitative forecasting approach without any judgemental indicators because of their more accessible data collection.

One might argue that the three categories require judgemental indicators to grasp the construct in focus because non-judgemental indicators might not express the constructs sufficiently in numbers. Therefore, the importance of the judgemental indicators is emphasized, and using them in a hybrid approach is recommended.

This issue can only be explored and thoroughly discussed by broadening the scientific literature reviews to other branches focusing on the categories mentioned above, and repeating the data selection funnel. However, to conclude the discussion from my current standpoint: the selection of the scientific branches was incomplete to fully cover the 14 categories with the judgemental or non-judgemental indicators separately. Not even all building blocks have been covered by each set of indicators separately.

Implications of the findings for the framework by Ortt & Kamp

However, the matching of the indicators and 14 categories also has significance for the framework by Ortt and Kamp. Although the framework had been designed for a different purpose (see Section 3.7.1), after an extensive literature review, all indicators could have been clustered into one of the 13 factors (excluding accidents and events because of being defined as unpredictable). Therefore, the framework by Ortt and Kamp also works as a starting point for predicting the start of large-scale diffusion. The earlier made assumption that the 14 factors would cover the whole environment around an innovation, innovating firm, and the innovation itself can be confirmed.

Additionally to the completeness check with the 13 categories, validation interviews have been done to confirm or reject the findings based upon an application to the green hydrogen sector. A detailed discussion of the answers to the interview questions can be found in Section 6.3.2. In conclusion, the following indicators were missing for the application of the forecasting approach on green hydrogen according to the interviewees:

- Dividing product price in CAPEX and OPEX
- Ease of use
- Competitiveness to other alternatives
- Sustainability impact
- Actor influence

Therefore, the assumption that the scientific literature would yield a complete list of indicators covering the entire environment for all kinds of radically new high-tech innovations has to be rejected.

Another topic that should be addressed regarding the completeness is that indicators that had a neutral rating on average in the selection criteria were added to the final list of indicators. It was argued that the list of indicators works as an offer to the user of the forecasting approach. In this case, and given the novelty of this research topic, it was decided to also include doubtful indicators, with a rating close to neutral, that might or might not predict than accidentally excluding an indicator that would have worked well in reality. This decision has to be seen as critical. A user of the forecasting approach could now work with insufficient indicators. A practical application of the indicators is needed to see if all indicators which have been selected predict and work practically well (more about the practical validation comes in Section 7.3.5). This critic also brings us to the following topic: currently, little knowledge exists about how the indicators predict. However, beforehand tasks for future research on the methodology are discussed.

Future research for the methodology

Although the validation has shown that many indicators per category were found, there is still room for improvement for:

- The non-judgemental indicators in the categories:
    - Complementary products & services
    - Innovation specific institutions
    - Natural, human & financial resources
- The application on green hydrogen:
    - Dividing product price in CAPEX and OPEX
    - Ease of use
    - Competitiveness to other alternatives
    - Sustainability impact
    - Actor influence

More indicators can be found by broadening the exploration phase and using the entire data collection cube. This research focused on six scientific branches. For the data collection, the other two sources (case studies and expert interviews) remained untouched. It is recommended to restart the exploration phase by emphasizing case studies and expert interviews to increase the number of available indicators in all categories. Especially expert interviews can be an excellent option to explore new knowledge about the pre-diffusion phase, which has not been published in scientific literature. However, also case studies work well if the next researcher would like to focus on one innovation. Case studies usually explore only one innovation in detail. However, even interviews can go into detail about one technology if experts from the industry in focus are interviewed (comparable to the green hydrogen validation interviews). The findings can be highly relevant for one technology but not fully generalizable to other innovations.

A third option available is to do literature reviews strictly focusing on the three categories mentioned above. Although six literature reviews have already been conducted in this master thesis, emphasising complementary products & services, innovation specific institutions, and natural, human & financial resources might help find non-judgemental indicators in these categories.

At the beginning of the thesis, the scientific branches to be analysed have been declared (see Section 2.1.1). The scientific branches sustainable innovations, technology assessment, and technology readiness levels have been excluded from the literature reviews because they did not have strong relevance for the initial exploration of the research objective. However, the branches might reveal new insights which have not been found until now. Especially the sustainable innovations branch could be highly relevant for innovations concerning our environment, such as green hydrogen.

It is advisable to review these literature branches mentioned above and conduct interviews and case studies concerning the innovation in focus, if required. Indicators derived from these sources must enter the data selection funnel as a tool for selecting the most potential indicators. If they adhere to the criteria mentioned in the data selection funnel, additional indicators can be added to the forecasting approach.

7.3.2 Indicators

The completeness of the indicators has already been discussed as part of the methodology discussion. However, an issue that affects the indicators directly is how the indicators actually predict. This thesis has compiled a list of indicators that can foresee the upcoming start of large-scale diffusion. However, an actual prediction of when an innovation will diffuse is in the current state not possible. Currently, the forecasting approach is mainly relevant for other researchers as a starting point of their work. However, it should not be forgotten in the consecutive work that how an indicator predicts depends on the forecasting technique. While a threshold might be correct for assumptions-based modelling, another approach signalling the start of diffusion might be needed for the regression models.

Another issue related to the actual prediction is the concept of predicting the start of diffusion based upon a combination of indicators. For example, a prediction might not be possible by looking at the indicators P*roduct price* and *New firm entry* separately. However, seeing the two indicators in combination could be a good predictor for the start of large-scale diffusion. This argumentation follows the research by Agarwal and Bayus (2002), which in fact have described the combination of the indicators *Product price* and *New firm entry*.

During the validation interviews, candidates were interested in which indicators have the most impact on the large-scale diffusion (see Section 6.3). This information would help governments institutions and companies to focus their efforts on a quicker diffusion. How such an analysis can be conducted is explained in the box below.

Future research for the indicators

For the indicators, two limitations exist, which should be explored in future work. Foremost, the most critical limitation is the missing knowledge of how the indicators exactly predict the start of large-scale diffusion. The indicators have been selected because they observe and anticipate the start of diffusion. However, an actual prediction is practically not possible in the current state. Therefore, more research is required on how the indicators predict in combination with the five forecasting techniques.

This prediction can be researched very detailed via a qualitative analysis based on case studies, each focusing on one innovation. Changes in the indicator value over time might explain under what conditions an innovation diffuses (see Figure 42). Also, thresholds per indicator might exist. If a threshold is crossed, the diffusion is not hampered anymore. The findings from the different case studies can be compared visually in time series, conclusions drawn, and findings generalized to apply to a wide range of radically new high-tech innovations.

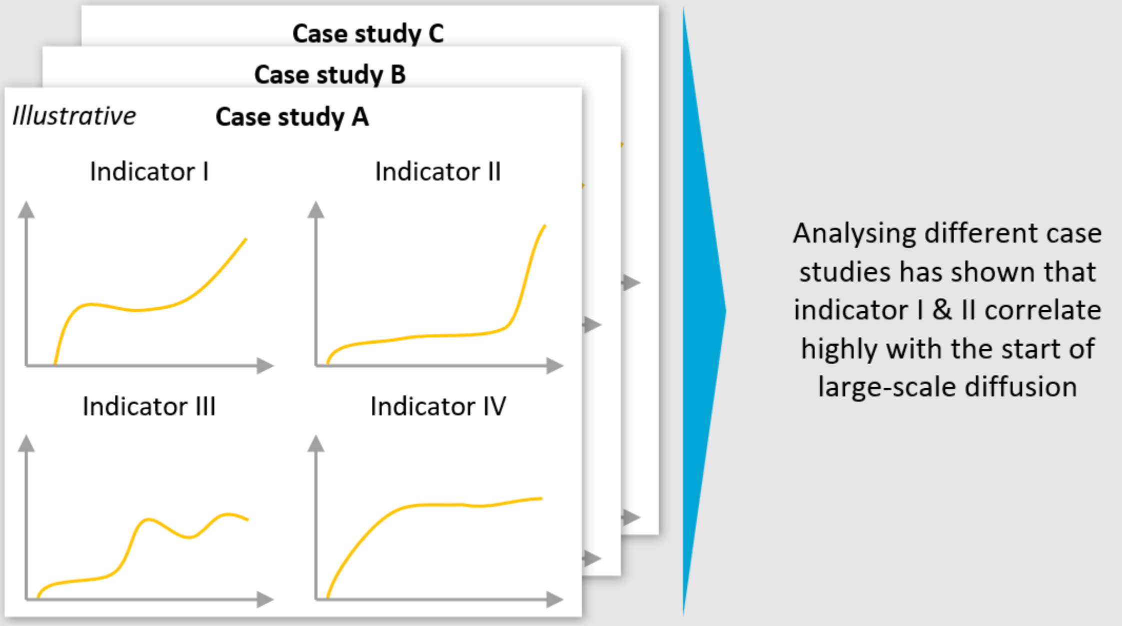


Figure 42: Visualization of the future research for the indicators

Nevertheless, not only a visual comparison of the indicators can reveal the threshold or relevance for the prediction. For example, a quantitative correlation analysis between each indicator and the market share could show which indicator correlates well with the start of large-scale diffusion. Later, a factor analysis could reduce the number of indicators to a few variables to improve the handling of the indicators. The factor analysis could also reveal more insights about the decisive indicators and create transparency for the diffusion process.

While exploring the indicators and their predictiveness, the researcher should pay careful attention to a hype-cycle behaviour for judgemental indicators (see Section 6.3.2). A longitudinal study might be required to fully comprehend the effect of trends and hypes on the judgemental indicators (see Figure 43). Experts are asked to evaluate the judgemental indicators of an innovation during the pre-diffusion phase. Then, after the diffusion, the experts re-evaluate the judgemental indicators for the earlier time point but including more recent knowledge. The effects of a hype or trend are likely not prevailing during the second evaluation and, therefore, the results will be trend-adjusted. In collaboration with the experts, the researcher could then distinguish between an indicator value influenced by the hype, if a large discrepancy between the values exists, and an indicator value not influenced by the hype.

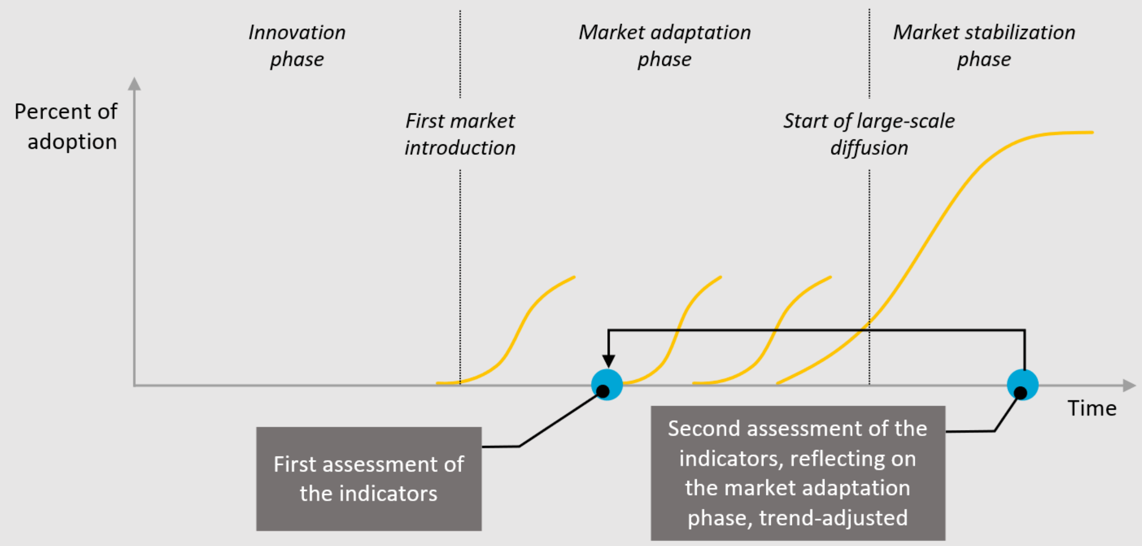


Figure 43: Longitudinal study hype-cycle behaviour

Additionally, during this extended research, relationships between the indicators should be considered. For example, it could be possible that only a specific combination of indicators crossing a certain threshold start the diffusion (compare the research by Agarwal & Bayus, 2002). A similar behaviour might be possible for other indicators. One indicator might influence the increase in another indicator which subsequently could lead to diffusion. Such information is highly relevant for the diffusion prediction as a chain of reaction might be started by one of the indicators measuring a mechanism in the pre-diffusion phase. Initial findings of relationships between indicators shown in Appendix D can be used to start the research about the relationships between indicators.

Another relevant discussion that came up during the validation interviews was which would be the most critical indicator for diffusion. Knowing this indicator could improve the forecasting of the start of diffusion, as well as give companies a better understanding and guidance to set focus points for their diffusion strategy.

Two research strategies are possible to explore this topic. First, it could be assumed that the last radically changing indicator before diffusion could be the most important one because that indicator blocks the diffusion until the end. Various case studies would be required to find the last changing indicator among a variety of innovations. However, this assumption might be flawed because the last changing indicator does not automatically mean that the indicator has much relevance for the diffusion. Its change in value might be arbitrary or due to the indicator's definition.

A better research strategy would be to rank the indicators according to their importance in each category and the category itself. A recommended method to rank the indicators is the Best-Worst-method (BWM). The BWM is a multi-criteria decision-making method widely used in the dominant design branch (see research by van de Kaa et al., 2014, 2017, 2020). Different interviewees are asked to indicate the most important and least important indicator and subsequently compare the importance of the other indicators to the most and least important indicator (Rezaei, 2016). From my experience, the method works well with interviewees. It fits the research problem of finding the most crucial indicator upon alternatives based on experts' experience and objective criteria.

7.3.3 Criteria

The criteria to evaluate the indicators have been developed carefully as part of the data selection funnel (see Section 2.1.2). The eight criteria covered a wide range of questions one might have before using an indicator. By evaluating the indicators with the criteria, doubtful indicators with a poor rating were excluded.

From my perspective, all criteria were applicable to the indicators, and the interview candidates did not criticize any criteria during the validation interviews. Moreover, I have not received any criticizes while doing the expert interviews to rate the criterion *Prediction* and *Empirical proof*. All interviews were straightforward, and all results were usable for the remaining research.

During the rating of the indicators, it seemed that the criteria *Availability of data* and *Cost of data* would correlate highly. It looked like indicators that have much data available usually also have free or cheaper data sources. This correlation could create an issue because the selection of the indicators happened based on the criteria. Generally, if criteria correlated highly, the rating of the criteria would move together in the same direction (for positive correlations), although no causal relationship exists. Thus, indicators would be selected biased, and the criteria would be insufficient to select the indicators. To confirm this first observation, I performed a Pearson's *r* correlation analysis with all eight criteria for all 50 indicators in JASP.[15] The results are shown in Table 17.

The correlation analysis confirms the observation and shows the highest correlation among all criteria between Availability of data and Cost of data with an *r* of 0,784. One might explain this strong relationship because indicators that have data readily available also have lower costs to gather data. The same applies if indicators are judgemental, more time is required to gather data, increasing the costs for the data collection. Additionally, weaker correlations have been found between the criteria[16]:

- *Timeliness of prediction* and *Prediction*
- *Quantifiable and Objectivity* and *Availability of data*
- *Quantifiable and Objectivity* and *Cost of data*
- *Empirical proof* and *Timeliness of prediction*
- *Empirical proof* and *Quantifiable and Objectivity*

The first correlation, *Timeliness of prediction* and *Prediction*, can be explained with a bias towards indicators later in the timeline. A respondent might see an indicator as a better predictor if the indicator emerges later in the timeline. However, the correlation is somewhat weak, with an *r* of 0,308.

[15] JASP Version 0.14.1, Dec 2020

[16] The classification criteria have been excluded from this analysis because they have not been used to select indicators. However, their correlations between the criteria can be found in Table 17.

The following two correlations between the criteria *Quantifiable and Objectivity* and the *Availability of data* and *Cost of data*, respectively an *r* of 0,541 and 0,522, are also somewhat straightforward explained. More objective indicators require less time and have lower costs to collect data because their information is readily available.

The criteria *Empirical proof* and *Timeliness of prediction* have a negative correlation with an *r* of -0,463. This negative correlation means that the later the indicator emerges, the weaker is its empirical proof. This correlation might be explained because of the high number of patent-related indicators. These indicators have already been used by various diffusion models and emerge quite early in the pre-diffusion phase. Hence, due to the large fraction of patent indicators (9 out of 50), this relatively medium correlation appeared significant.

Lastly, also the relationship between the criteria *Empirical proof* and *Quantifiable and Objectivity* is simple to explain (*r* of 0,405). The non-judgemental indicators, which are more quantifiable and objective due to their definition, have a larger share of indicators that already have been used in a forecasting model. Therefore, they have better empirical proof than the judgemental indicators that mainly have been derived from literature and have not been used before.

Table 17: Correlations between the criteria

P=Prediction; TP=Timeliness of prediction; AD=Availability of data; CD=Cost of data; Q&O=Quantifiable and objectivity; EP=Empirical proof; G=Generalizability; S=Simplicity

Criteria		P	TP	AD	CD	Q&O	EP	G
P	Pearson's r	—						
	p-value	—						
TP	Pearson's r	0,308*	—					
	p-value	0,030	—					
AD	Pearson's r	0,075	-0,126	—				
	p-value	0,604	0,382	—				
CD	Pearson's r	0,090	-0,051	0,784***	—			
	p-value	0,534	0,727	< ,001	—			
Q&O	Pearson's r	0,082	-0,026	0,541***	0,522***	—		
	p-value	0,573	0,857	< ,001	< ,001	—		
EP	Pearson's r	-0,029	-0,463***	0,237	0,263	0,405**	—	
	p-value	0,840	< ,001	0,097	0,065	0,004	—	
G	Pearson's r	-0,064	-0,394**	-0,013	-0,138	-0,028	0,411**	—
	p-value	0,660	0,005	0,930	0,338	0,849	0,003	—
S	Pearson's r	0,104	-0,195	0,684***	0,630***	0,691***	0,498***	0,054
	p-value	0,471	0,174	< ,001	< ,001	< ,001	< ,001	0,707

** p < ,05; ** p < ,01; *** p < ,001*

Especially the strong correlation between the criteria *Availability of data* and *Cost of data* might be an issue for an unbiased selection of indicators. However, the data underlying the indicator plays a significant role while using the forecasting approach. An indicator cannot be used if data is unavailable or the costs outweigh the value of the forecast. Additionally, a sensitivity analysis was performed, and selection mechanism Version 5 emphasised the independent rating of the criteria *Prediction*. The criterion *Prediction* only has a weak relationship with the *Timeliness of prediction*. Therefore, the correlation with *Prediction* can be neglected, and the strong correlation between *Availability* and *Cost of data* might be less severe for the outcome of this research.

The other significant correlations are even weaker, with the highest *r* of 0,541. Therefore, also these correlations are less relevant for the results of the selection process. However, more research might be needed to confirm these assumptions.

Nevertheless, the eight criteria at the end of the data selection funnel were not the only criteria used in this research. The first step in the data selection funnel was used to select the scientific branches. As the next paragraph will show in more detail, a broader selection criterion would have been better to cover the categories for the non-judgemental indicators fully. In contrast to that, the criteria of the second step worked well. Two criteria were used to pre-select indicators that did not apply to the research objective of predicting the start of large-scale diffusion. Especially in the dominant design branch, indicators had to be removed because they did not measure constructs related to timeliness. Although it is hard to evaluate this decision alone, my mentors have agreed to exclude the not relevant indicators in the dominant design branch. Based on this confirmation, I would reinforce the decision of using the criteria because of their correct outcome.

Additionally to the concerns, candidate D of the validation interviews asked if an overlapping between the indicators existed. For example, two or more indicators could measure the same construct, leading to an overweighing of this construct in a forecast. This question would require a new criterion that measures how much overlap between indicators exists. How the new criterion *Overlap* can be analysed per indicator is explained in the box below. The interview candidates have not mentioned other additions to the criteria in the validation interviews.

Future research for the criteria

Not much future research is required for the criteria, as the analysis and discussion have shown that the criteria worked well in ranking the indicators. However, six correlations between the criteria, especially between the *Availability and Cost of data*, have been found. Argumentations that have been described earlier found these correlations as non-critical. However, a future researcher might explore the effect of the correlations on the research outcome in more detail by examining the correlations qualitatively better and using an external perspective besides me.

Additionally, to evaluate the new criterion *Overlap,* a new research strategy is required. Two possibilities are available: a qualitative or more quantitative analysis. The qualitative analysis can be done by a researcher based upon the relationships between the indicators shown in Appendix D. A researcher could compare the interconnectedness of the indicators and declare them as overlapping if solid qualitative evidence exists. In the quantitative approach, a researcher could analyse correlations of indicators in different case studies and compare the correlations among the case studies. If a strong correlation exists between two indicators, the researcher should analyse the indicators and decide if this correlation appeared causally or arbitrary. The final decision over the *Overlap* would be still qualitative in this approach but backed by quantitative data.

7.3.4 Forecasting approach

The forecasting approach has a limitation towards selecting the suitable regression model. Currently, three regression models (Cox, Logistic, and Gompertz regression) have been combined into one category. As already mentioned in Section 3.1.2, a decision between these regression models is highly case dependent. However, more research could elaborate on this case dependency and add to the forecasting approach's decision tree.

Another question that occurs is if the forecasting techniques are complete as such. After the literature review over the forecasting techniques, all appropriate methods have been used for the forecasting approach. However, the collection of methods could be outdated soon due to the increasing interest in predicting behaviour or scenarios in recent years. Especially the methods based on machine learning are still being explored, and new methods might occur anytime soon.

Additionally, while answering the main research question, it has already been described that the forecasting approach is not usable for companies in the current state. More scientific work is needed to turn the basis of this research into a framework and model that can predict the start of large-scale diffusion. However, more practical issues also have to be resolved to make the research usable for a company. The current use of the forecasting approach is rather rough, and something more tangible is required to create a better forecasting experience for a company.

Lastly, during the interview, candidate B recommended adding a modelling feature to the forecasting approach. This would allow companies to forecast the start of large-scale diffusion and develop different scenarios based on the modelling. This addition has also been described in the literature under a “what-if” analysis by Goodwin. “[…] Rather than producing a single forecast based on a fixed set of assumptions, forecasting models will have their greatest value if they can provide ‘what-if’ estimates of future adoptions enabling managers to estimate the effect of alternative strategies and hence make decisions which will maximise the chances of a product’s success” (Goodwin et al., 2014, p. 42).

Future research for the forecasting approach

For the forecasting approach, more research is required for the regression models. The recommended use of the regression models (Cox, Logistic, and Gompertz regression) is dependent on the case. To give a user of the forecasting approach better guidance, which regression model to choose in what scenario, literature research in the forecasting field, and expert interviews with forecasting specialists can clear the unclarity. Afterwards, this knowledge can be added to the decision tree of the forecasting approach.

Moreover, something more tangible is required to make the forecasting a better user experience. For example, a software package including all required modules to forecast the start of diffusion and an interface for each forecasting technique would improve the usability of this research for companies. An employee could load all data into the software and select its preferred forecasting technique. The software would then calculate the forecast and show time series graphs for the indicator data to improve the transparency of the forecast.

Additionally, one of the software packages can include the what-if analysis. This package would provide a graphical user interface in which a user can enter estimates for specific indicators. Based on these estimates, a forecast for a certain scenario could be forecasted, providing companies more insights into the forecast and giving managers a quantitative analysis to prepare a market entry strategy.

7.3.5 Validation

As described before, careful attention has been paid to the validity of the research. This attention is essential because the methodology used for the master thesis is focused on desk research. Empirical research that allows observations first-hand was not possible due to the limited timeframe and social distancing measures when I started my work. Given these conditions, the best options have been chosen to ensure validity throughout the research, as well as validating the framework afterwards. For example, the empirical proof of an indicator was a decisive criterion while selecting the indicators. Additionally, a scientific and practical quality gate has been used to select the indicators and to evaluate and validate the forecasting approach, indicators, and criteria in expert interviews, respectively. Different interview candidates have been asked to ensure the interviews' scientific or practical aim for each quality gate. Which other measures have been taken to ensure the rigour of the research has been explained in Section 2.1.3.

However, the final validation method of the forecasting approach does not the meet highest standards. The research has been applied to two fictional case studies as an illustration, to show how the forecasting approach works. Additionally, expert interviews for the validation, the already mentioned practical quality gate, have been conducted to confirm or reject the findings and to receive an outside perspective of practitioners. These interviews provided great insights into the application of the green hydrogen case, and the candidates have articulated valuable remarks to improve the forecasting approach. However, an actual application of the model by an external researcher or company would have been better for the validation due to various reasons:

- Less bias
- An external perspective of a user
- A real case study
- Comparability between forecast and reality

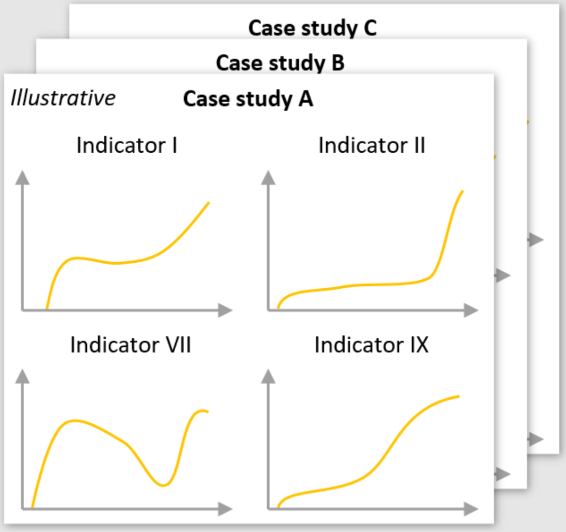
The interview candidates have also criticized the form of validation in this master thesis. The robustness of the forecasting approach is highly valued by candidates C and D (2021; 2021). Moreover, candidates B and C (2021; 2021) mentioned that the forecast of the start of large-scale diffusion could influence investment decisions. Hence, a robust validation method is required. How the forecasting approach can be validated better is explained in the box below.

Future research for the validation

As already mentioned various times in the thesis, the validation methods used in this thesis are only adequate given the limited time. However, an actual application of the forecasting approach to an existing innovation is necessary to confirm the research's validity thoroughly. This research could be combined with the case studies required to describe how the indicators predict (see Section 7.3.2). While applying the forecasting approach on a case to find and explore the behaviour of the indicators over time, one can get a clear picture of the validity of the forecasting approach and its issues.

In my opinion, to validate the forecasting approach empirically, only a few case studies per forecasting method (about three) are required. A user will realize in a short time if errors in the decision tree exist or if indicators do not fit the forecasting technique. However, if the forecasting approach will be turned into a forecasting framework, including the prediction based on the indicators, the number of case studies increases drastically. Empirical validation of the extended research might be possible by examining more than 20 historical case studies per forecasting method due to the complexity of the topic. Predicting the start of diffusion is not a simple task, and each case study might be unique with different results. Therefore, such a high number of case studies is needed to remove outliers in the research and draw conclusions on the findings. The more cases are studied, the higher is the value of the validation and the model’s trustworthiness increases.

To validate the forecasting framework empirically, a researcher would select historical case studies of radically new high-tech innovations. It is essential for the validation that the start of diffusion has already passed. Historical case studies allow a comparison of the projected time point compared to the actual time point. After selecting the case studies, the researcher would predict the start of large-scale diffusion given the knowledge and data during the pre-diffusion phase (see Figure 44). Afterwards, the researcher would compare the predicted start of large-scale diffusion with the actual start. If the time points match closely, the framework is validated and proven. It would be advisable to predict the time point of large-scale diffusion per case study multiple times, each from a different time point during the pre-diffusion phase. Then, the researcher could find out how early a prediction with the framework is reliable.



Case study	Predicted start of diffusion (3 years before)	Actual start of diffusion
A	2020	2020
B	2007	2003
C	2015	2016

Prediction of case study A and C matches the historical timepoint closely; for case study B the time point was predicted falsely

Figure 44: Visualization of the recommended validation

In the next section, the scientific contribution of the master thesis is explained, and the tasks for future research are summarized and ordered chronologically.

7.4 Scientific contribution and summary of future research

This last section of the thesis will explain the scientific contribution of the research and summarize the tasks for future research explained in the previous section. The thesis is laying the foundation for future research in the field of forecasting the start of large-scale diffusion of radically new high-tech innovations by adding the following contributions to the scientific field:

- Designing a research methodology to derive indicators and select them deliberately
- Developing criteria to evaluate predictive indicators
- Giving an overview of relevant forecasting techniques
- Describing characteristics, advantages, and disadvantages of the forecasting techniques
- Guiding researchers and practitioners towards a forecasting technique and its indicators based upon a forecasting approach incorporating hybrid approaches of forecasting techniques
- Deriving and evaluating independent variables for the prediction of the start of large-scale diffusion

Figure 45 gives a visual overview of what has been accomplished in this thesis and what is missing to fully answer the main research question. The foundations have been finalized with limitations for the criteria and predictive indicators due to incompleteness (see Section 7.3.2 and 7.3.3). The validation for the current components is partly fulfilled. An extended real validation of the forecast is required once the indicators can predict the start of large-scale diffusion. Additionally to the already mentioned contributions, the thesis has implications for the research by Ortt & Kamp. The framework they developed for a different use case also aids a researcher to predict the start of diffusion (see the detailed explanation in Section 7.3.1).

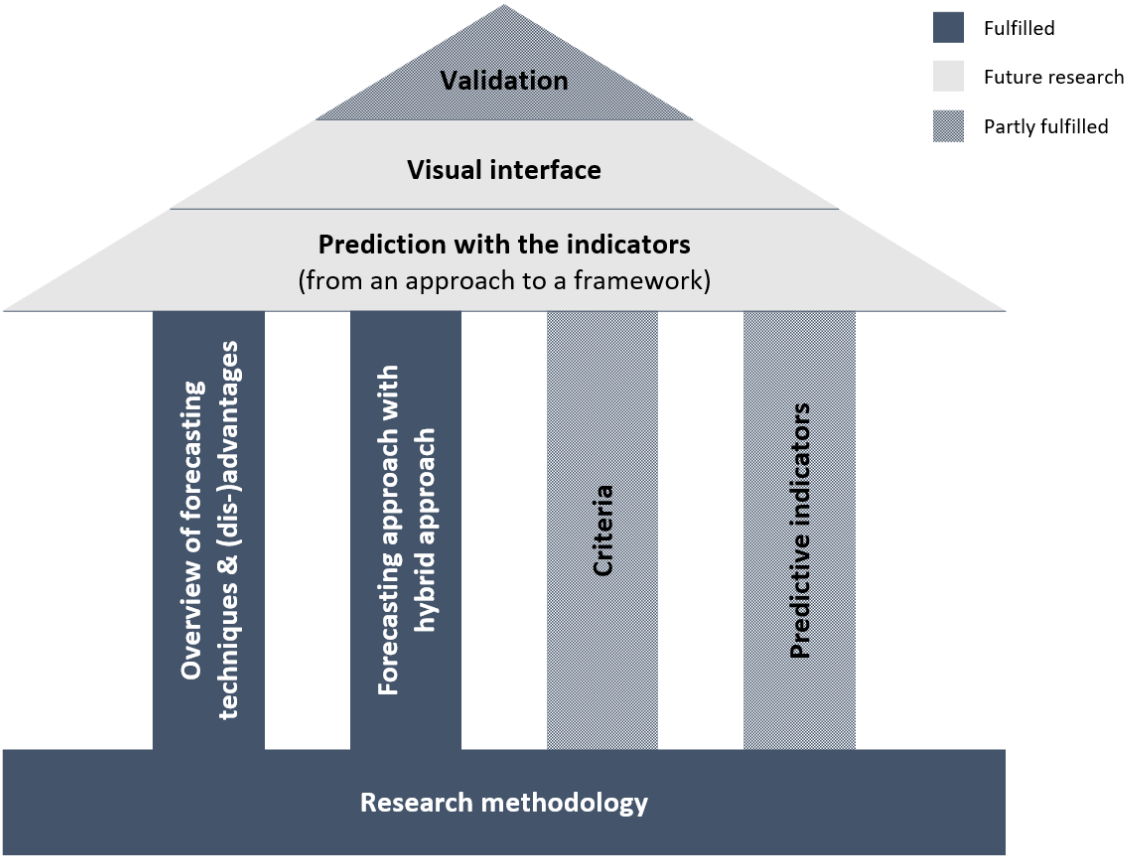


Figure 45: Overview scientific contributions

Additionally to the basis laid out with the master thesis, required and optional tasks for future research are recommended. Required tasks are reflected as grey blocks in Figure 45; additional research tasks are not shown.

Tasks have been ordered according to their logical way of completion to ease the start for a subsequent researcher. First, the application of the methodology has to be broadened by covering more scientific branches to increase the number of indicators in insufficient categories. Secondly, the criteria must be improved by clearing out doubts of correlation and adding the criterion *Overlap*. Afterwards, the most important step is required: Turning the forecasting approach into a forecasting framework by explaining how the indicators actually predict the start of large-scale diffusion. Lastly, the validation must be improved by deploying a longitudinal study for the judgemental indicators to rule out the influence of trends and validating the entire framework thoroughly by studying historical case studies. Research tasks that are optional depending on the innovation to be predicted (for example, green hydrogen) or extra features to the forecast (such as the modelling) are shown in grey in the list below. The following seven research tasks are necessarily recommended, alongside five optional tasks in grey:

1. Explore scientific branches to find non-judgemental indicators (all radically new high-tech innovations) focusing on
    a. Complementary products & services
    b. Innovation specific institutions
    c. Natural, human & financial resources

2. Explore the scientific branch sustainable innovations to find additional indicators (sustainable products focused)
3. Go through the data selection funnel for the following indicators (green hydrogen focused)
    a. Dividing product price in CAPEX and OPEX
    b. Ease of use
    c. Competitiveness to other alternatives
    d. Sustainability impact
    e. Actor influence
4. Conduct expert interviews and case studies for a specific innovation to find additional indicators if required
5. Explore the criticality of the correlation between the criteria qualitatively
6. Evaluate indicators overlap by using whether the
    a. Qualitative approach by exploring relations between indicators
    b. Or the quantitative approach by exploring correlations between indicators
7. Define how indicators predict the start of large-scale diffusion in a correlation analysis to turn the forecasting approach into a forecasting framework
8. Explore which is the most decisive indicator for the diffusion by using whether the
    a. BWM approach
    b. Or a visual analysis
9. Add a visual interface for the forecasting framework to make it practically relevant for companies
10. Add a modelling feature to the forecasting framework
11. Explore if a hype-cycle behaviour exists for the judgemental indicators in a longitudinal study
12. Validate the forecasting framework by studying historical case studies and comparing the predicted and actual start of large-scale diffusion

Each of these steps has been explained in more detail in the previous Sections 7.3.1 to 7.3.5. I hope that this preparation of future research motivates other researchers to take up the task of predicting the start of large-scale diffusion.

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Appendix A: Quality of the systematic literature review

Table 18: H-Index and SCImago Journal Rank 2019

Journal	Article	H-index of the journal	SCImago Journal Rank 2019
Annals of Operations Research	(Zhang, Tian, & Fan, 2020)	96	Q1 (1,12)
Australasian Marketing Journal	(Chumnumpan & Shi, 2019)	32	Q2 (0,48)
Book: Gaining Momentum: Managing the Diffusion of Innovations	(Ortt, 2010)	N/A	
Book: Wiley International Encyclopedia of Marketing	(Kahn, 2010)		
Conference PICMET 2009 Proceedings	(Fallah et al., 2009)		
Conference PICMET 2018 Proceedings	(Duwe et al., 2018)		
Conference: IAMOT 2007 Proceedings	(Ortt et al., 2007)		
Conference: ICIS 2010 Proceedings	(Rui et al., 2010)		
Conference: ISPIM Innovation Summit 2015 Proceedings	(Ortt et al., 2014)		
Conference: Proceedings of the 2nd international conference on Knowledge capture	(Nasukawa & Yi, 2003)		
Decision Support Systems	(van Steenbergen & Mes, 2020)	138	Q1 (1,92)
ECB Working Paper No. 1275	(Banbura et al., 2010)	N/A	
Expert Systems with Applications	(Tseng & Hu, 2009)	184	Q1 (1,49)
IEEE Transactions on Engineering Management	(Kanniainen et al., 2011)	89	Q1 (1,07)
IMA Journal of Management Mathematics	(Goodwin et al., 2013)	30	Q1 (0,91)
Industrial Management and Data Systems	(D. Kim et al., 2019; T. Kim et al., 2016)	96	Q1 (1,39)

Table 18 (continued)

Intangible Capital	(Mas-Machuca et al., 2014)	13	Q3 (0,27)
International Journal of Forecasting	(Goodwin et al., 2014; Meade & Islam, 2006)	85	Q1 (1,75)
International Journal of Research in Marketing	(Peres et al., 2010)	95	Q1 (2,91)
Journal of Business Research	(Fan et al., 2017; Hyman, 1988; Kang et al., 2020)	179	Q1 (1,87)
Journal of Forecasting	(Bottomley & Fildes, 1998)	55	Q2 (0,65)
Journal of Grey System	(Guo et al., 2015)	13	Q3 (0,30)
Journal of Product Innovation Management	(Bayus et al., 2007; Garcia & Calantone, 2002)	135	Q1 (3,13)
Kybernetes	(Yin et al., 2020)	37	Q1 (0,38)
Management Science	(Agarwal & Bayus, 2002; Bass, 1969, 2004)	237	Q1 (5,44)
Marketing Letters	(B. C. Lee et al., 2020)	65	Q1 (1,41)
Marketing Science	(Chandrasekaran & Tellis, 2007; Golder & Tellis, 1997, 2004; Markovitch & Golder, 2008; Sood et al., 2009)	120	Q1 (7,17)
PLOS ONE	(W. S. Lee et al., 2018)	300	Q1 (1,02)
Research in Transportation Economics	(Massiani & Gohs, 2015)	39	Q1 (0,85)
Review of Economic Studies	(Heckman & Singer, 1984)	133	Q1 (14,24)
Review of Marketing Research	(Libai et al., 2009)	15	Q4 (0,18)
Soft Computing	(Zhang, Tian, Fan, et al., 2020)	73	Q2 (0,71)
Sustainability	(Yang et al., 2020)	68	Q2 (0,58)
Technological Forecasting and Social Change	(Daim et al., 2006; Fernández-Durán, 2014; Ilonen et al., 2006; C. Lee et al., 2018; H. Lee et al., 2014; Mahajan & Muller, 1996; Muller & Yogev, 2006)	103	Q1 (1,82)
Technology Analysis & Strategic Management	(Schot & Geels, 2008)	64	Q2 (0,63)

H-index and SCImago Journal Rank 2019 provided by SCImago Journal & Country Rank (https://www.scimagojr.com/)

All articles except for three have been classified in the first or second quartile, Q1 or Q2 respectively, in their research area with a relatively high h-index. However, a few journals in the category Q1 or Q2 have a relatively low h-index which can be explained by special interest journals covering only a small research area with less published work and low citations.

Critical classification of articles published in journals ranked as Q3 or Q4:

- Guo et al. (2015) has only be mentioned to show the variety of novel approaches incorporating old findings. The work shown in the articles has not been used.
- Libai et al. (2009) has only been included to explain the discussion around cross-market communication. Furthermore, the article was co-authored by Mahajan and Muller, two influential and respected researchers in the field of predictive models.
- Mas-Machuca et al. (2014) has only be used to give an initial overview of the topic, refine search terms, and classify Kahn’s categories (2010).

Books, conference papers, and working papers are not assessed by the SCImago Journal Rank. However, the two books are made available by respected scientific publishers. For the conference papers, it is difficult to assess the quality. However, researchers have been assessed before presenting at a conference to the public. The working paper's credibility is guaranteed by the publishing institution, the European Central Bank.

Appendix B: Detailed indicator evaluation per expert

Table 19: Detailed indicator evaluation per expert

Indicator	Prediction			Average
	Expert 1	Expert 2	Expert 3	
Frequency of product changes decreases	5	4	1	3,33
Predecessor's growth slows down	5	3	5	4,33
Dominant category selected	3	3	2	2,67
Dominant design selected	5	1	1	2,33
Number of product categories decreases	3	4	2	3,00
Standards exist	4	4	1	3,00
Complementary products and services available	5	4	5	4,67
A problem to be solved exists	3	4	3	3,33
Critical mass reached	5	4	1	3,33
Sentiment of internet forums	5	3	3	3,67
Size of the market	2	4	4	3,33
Bandwagon effect	4	3	5	4,00
Network externalities	4	3	5	4,00
Associations, coalitions, or groups formed	5	2	4	3,67
Laws and Regulation	3	3	2	2,67
Identified as a megatrend	3	4	5	4,00
Number of articles in the popular media	3	3	5	3,67
Certain customer requirements	5	4	5	4,67
Bibliometric data	5	3	4	4,00
Certain product specifications	5	4	4	4,33
Development effort and capabilities	3	4	3	3,33
Education	2	4	4	3,33
Forward citations of patents	5	3	5	4,33
Novelty of the patent	2	3	5	3,33
Patent growth speed	5	3	5	4,33
Quality of patents	3	3	4	3,33
Quantity of patents	4	3	5	4,00
Science-intensity	2	3	5	3,33
Scope and coverage of patents	4	3	4	3,67
Abnormal stock returns	5	3	4	4,00
Purchasing power	2	4	4	3,33
Coefficient of innovation	3	3	4	3,33
Availability of materials, suppliers, etc	2	4	5	3,67
Number of product announcements	5	4	4	4,33
Number of trade fair presentations	5	4	5	4,67
Coefficient of imitation	5	3	4	4,00
New firm entry	5	4	4	4,33
New incumbent firm entry	5	4	2	3,67
Market penetration	2	3	2	2,33
Year of introduction	2	1	3	2,00
Sentiment of the popular media	5	3	5	4,33

Table 19 (continued)

Number of online reviews	4	3	4	3,67
Number of product reviews in the media	4	3	5	4,00
Sentiment of online reviews	5	3	3	3,67
Product performance increases	5	4	5	4,67
Product price decreases	5	4	2	3,67
Switching costs	2	1	2	1,67
Automatization of production increases	5	4	1	3,33
Production capacity increases	5	4	1	3,33
Supportive niche communities	2	4	2	2,67

Appendix C: Results from the sensitivity analysis

Indicators with a grey shading have been excluded by the corresponding selection mechanism (see Table 20). The cut-off values for each version are explained below:

Version 1: Indicators with an overall value lower than 15 (in each of the five summed up criteria a neutral rating) will be excluded.

Version 2: Indicators with an overall value below 12 (in each of the four summed up criteria a neutral rating) will be excluded.

Version 3: Indicators with an overall value below 15 (in each of the five summed up criteria a neutral rating) will be excluded.

Version 4: Indicators with an overall value lower than 45 (in each of the five summed up criteria and the Prediction criterion a neutral rating) will be excluded.

Version 5: Indicators with an overall value below 36 (in each of the four summed up criteria and the Prediction criterion a neutral rating) will be excluded.

Table 20: Results from the sensitivity analysis

Indicator	Version 1	Version 2	Version 3	Version 4	Version 5
Frequency of product changes decreases	18	13	18	60,0	43,3
Predecessor's growth slows down	20	15	20	86,7	65,0
Dominant category selected	0	0	0	50,7	37,3
Dominant design selected	0	0	0	32,7	0,0
Number of product categories decreases	19	15	19	57,0	45,0
Standards exist	22	18	22	66,0	54,0
Complementary products and services available	20	15	20	93,3	70,0
A problem to be solved exists	11	8	11	36,7	26,7
Critical mass reached	15	10	15	50,0	33,3
Sentiment of internet forums	20	15	20	73,3	55,0
Size of the market	0	0	16	53,3	0,0
Bandwagon effect	16	11	16	64,0	44,0
Network externalities	16	11	16	64,0	44,0
Associations, coalitions, or groups formed	17	14	17	62,3	51,3
Laws and Regulation	0	0	0	50,7	37,3
Identified as a megatrend	13	10	13	52,0	40,0
Number of articles in the popular media	22	18	22	80,7	66,0
Certain customer requirements	17	12	17	79,3	56,0
Bibliometric data	21	18	21	84,0	72,0
Certain product specifications	17	12	17	73,7	52,0
Development effort and capabilities	18	15	18	60,0	50,0
Education	13	0	13	43,3	0,0
Forward citations of patents	22	18	22	95,3	78,0
Novelty of the patent	21	18	21	70,0	60,0
Patent growth speed	21	18	21	91,0	78,0
Quality of patents	18	15	18	60,0	50,0
Quantity of patents	21	18	21	84,0	72,0
Science-intensity	21	18	21	70,0	60,0
Scope and coverage of patents	21	18	21	77,0	66,0

Table 20 (continued)

Abnormal stock returns	25	20	25	100,0	80,0
Purchasing power	23	18	23	76,7	60,0
Coefficient of innovation	0	0	15	50,0	0,0
Availability of materials, suppliers, etc	17	14	17	62,3	51,3
Number of product announcements	22	18	22	95,3	78,0
Number of trade fair presentations	21	17	21	98,0	79,3
Coefficient of imitation	0	0	18	72,0	0,0
New firm entry	23	19	23	99,7	82,3
New incumbent firm entry	24	19	24	88,0	69,7
Market penetration	0	0	0	46,7	0,0
Year of introduction	0	0	0	40,0	0,0
Sentiment of the popular media	18	14	18	78,0	60,7
Number of online reviews	23	18	23	84,3	66,0
Number of product reviews in the media	22	18	22	88,0	72,0
Sentiment of online reviews	20	15	20	73,3	55,0
Product performance increases	23	18	23	107,3	84,0
Product price decreases	24	19	24	88,0	69,7
Switching costs	0	0	0	31,7	23,3
Automatization of production increases	15	10	15	50,0	33,3
Production capacity increases	18	13	18	60,0	43,3
Supportive niche communities	0	0	0	45,3	32,0

Appendix D: Relationships between indicators

It is important to emphasize that indicators with a similar colour do not immediately have a causal relationship. They only likely move together in a similar direction. In the following paragraphs, I am going to explain the relationship between the linked indicators.

The indicators *Sentiment of internet forums* and *Supportive niche communities* have a bi-directional relationship (see Figure 46). For example, a supportive niche community is likely to be satisfied with a product. Additionally, nowadays, niche communities tend to not only discuss their hobby offline but also in online forums. Hence, a supportive niche community would also show their satisfaction online, which would be measurable with a sentiment analysis of online forums.

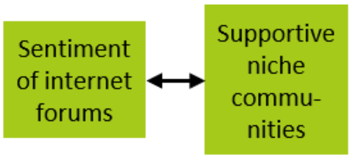

Figure 46: Relationship between the niche community indicators

A one-directional relationship exists between the indicators *Associations, coalitions or groups formed* and *Standards exist* (see Figure 47). Usually, coalitions are formed to agree on a standard allowing compatibility between products of different companies. Therefore, using an optimistic view, if coalitions are formed a standard will be defined on at a later timepoint.

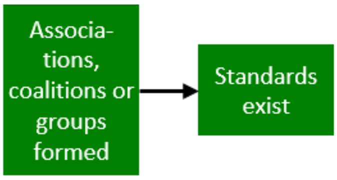

Figure 47: Relationship between the standards indicators

A special relationship exists between the indicators *New incumbent firm entry* and *New firm entry* (see Figure 48). The indicator incumbent firm entry is a sub-class of the new firm entry indicator. While the latter counts all firms entering a market with their product, the former indicator only counts incumbent firms.

Figure 48: Relationship between the new firm entry indicators

The indicators *Automatization of production system increases* and *Production capacity increases* have more loose one-directional relationship (see Figure 49). An expansion of the production system might be accompanied by an increase of the degree of automatization. A company expecting a mass-market entry would likely also switch from manual work to a more automatized production. However, the automatization possibility depends on the type of product or service.

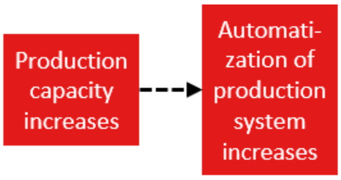

Figure 49: Relationship between production indicators

The relationship between the indicators *Identified as a megatrend* and *Number of articles in the popular media* is one-directional (see Figure 50). If an innovation has been identified as a megatrend, changing our current society, it is likely that the coverage in the popular media increases because the society and institutions have an aroused interest into the innovation.

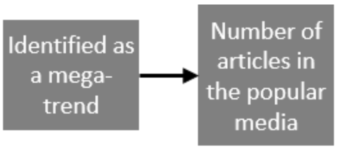

Figure 50: Relationship between megatrend indicators

The indicators *Patent growth speed*, *Quantity of patents*, and *Science-intensity* are bi-directional related to each other (see Figure 51). As all three indicators are based on the construct of increasing patent submissions, they all increase if one of the indicators is increasing. Additionally, the indicator *Development effort and capabilities* is one-directionally related to the other three indicators. First, the *Development effort and capabilities* of companies increase, which will subsequently increase the patent output for certain innovations. However, it should not be forgotten that every company or industry does not use patents due to high application and legal fees and lengthy processes.

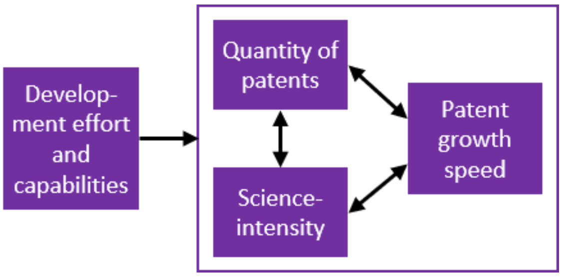

Figure 51: Relationship between patent indicators

Lastly, the indicators *Dominant category selected*, *Dominant design selected*, *Number of product categories decreases*, *Frequency of product changes decreases*, *Certain customer requirements*, and *Certain product specifications* have a more complex relationship. The one-directional connection between the indicators can be seen in Figure 52.

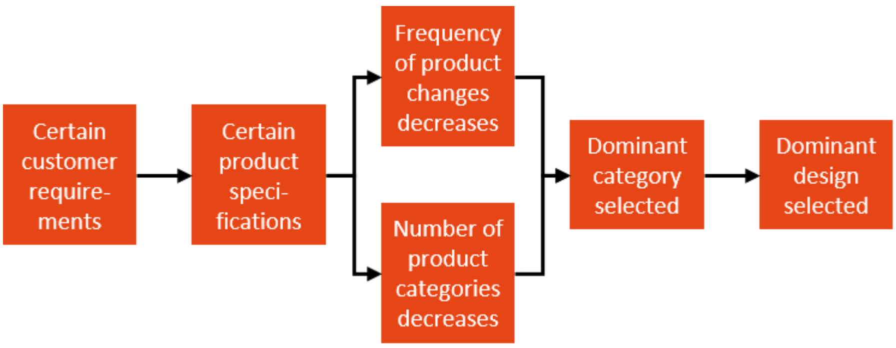

Figure 52: Relationship between the dominant design indicators

It starts with slowly emerging more certain customer requirements. From there, the product specification can be defined. More certain product specifications reduce the overall number of product categories but also the frequency of changes on a product level. Therefore, a dominant category materializes, which slowly will develop into a dominant design.

Appendix E: Validation interview protocol

The interview protocol for the validation interview consists of slides and questions per slide. The slides have been attached below.

Beginning

1. General information about the candidate
    a. What is your job? And where?
    b. What is your expertise?
    c. Since when do you work in the field? In various roles and companies?
    d. What is your level of education?
    e. What is your connection to hydrogen?

Page 4: Introduction

2. Do you think knowing the time point of large-scale diffusion helps researchers, companies, or government institutions? And how does it help?
3. In which stage do you see green hydrogen?
4. Do you predict or measure the development and diffusion of green hydrogen?
5. Which characteristics, factors or data do you observe for the development and diffusion of green hydrogen?

Page 6: Forecasting approach – First stage

6. Are the questions in the decision tree applicable and relevant for a company or researcher?

Page 7: Forecasting approach – Second stage

7. What is your opinion on the hybrid approaches to overcome disadvantages of the main forecasting technique?
8. Do you know alternatives to improve a forecasting technique?

Page 8: 13 categories

9. Do you know other building blocks or influencing factors which can predict the diffusion of green hydrogen?

Page 9: Non-judgmental indicators

10. Do you have comments to any of the indicator?
11. Are quantitative indicators missing?

Page 10: Judgmental indicators

12. Do you have comments to any of the indicator?
13. Are any judgmental indicators missing?
14. Do you agree with the initial assumption that the indicators can predict the start of large-scale diffusion?

Page 11: Criteria

15. Which information is relevant to know about an indicator? Which criteria would you use to evaluate the indicators?

Page 12: Criteria

16. Are criteria missing?

Page 13: Conclusion

17. Do you have general remarks to the forecasting approach?
18. How would you improve the concept?
19. Is the forecasting approach applicable to green hydrogen?
20. How can a company benefit from the forecasting approach?

Thesis Validation on Green Hydrogen

Florian Schmidt
Master thesis – Management of Technology

TU Delft

1

Agenda

- Introduction to the topic
- Research problem
- Forecasting approach
- Indicators
- Criteria to evaluate indicators
- Conclusion

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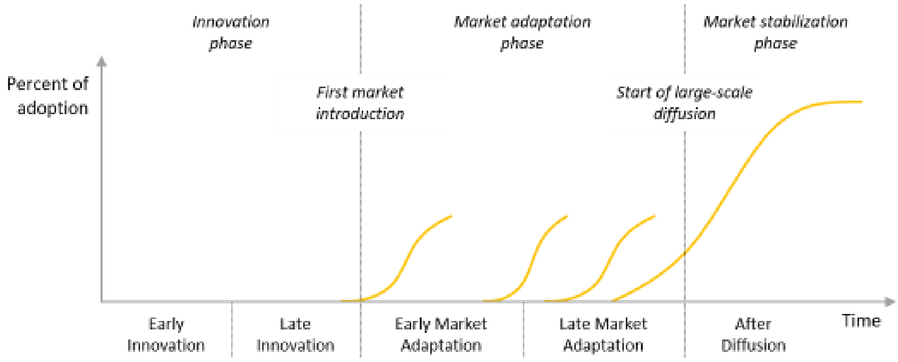
2

Introduction to the topic



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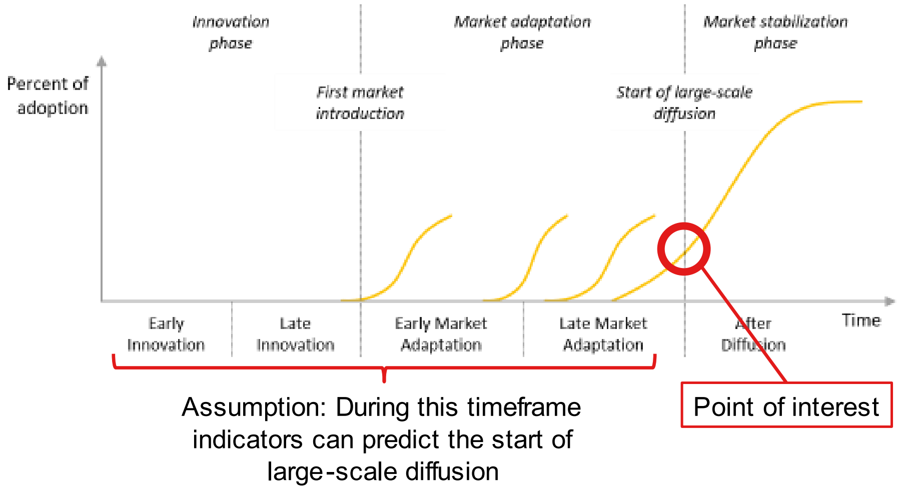
Source: Ortt, J. R., & Schoormans, J. P. L. (2004). The pattern of development and diffusion of breakthrough communication technologies. *European Journal of Innovation Management, 7*(4), 292-302.

3

Introduction to the topic



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Source: Ortt, J. R., & Schoormans, J. P. L. (2004). The pattern of development and diffusion of breakthrough communication technologies. *European Journal of Innovation Management, 7*(4), 292-302.

4

Research problem

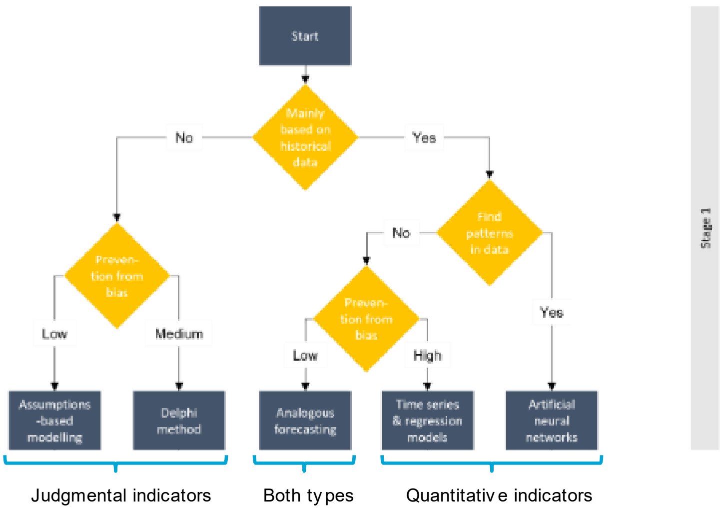
How can researchers and companies predict the upcoming large-scale diffusion of a radically new high-tech innovation?

To answer the question, I have developed a decision tree combining indicators as a first step for the prediction

The forecasting approach is applicable to many technologies but today we focus on green hydrogen

5

Forecasting approach– First stage



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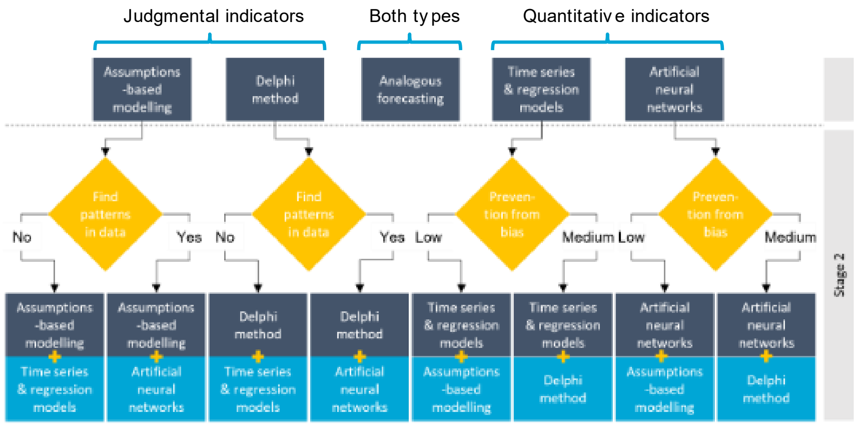
Forecasting approach– Second stage

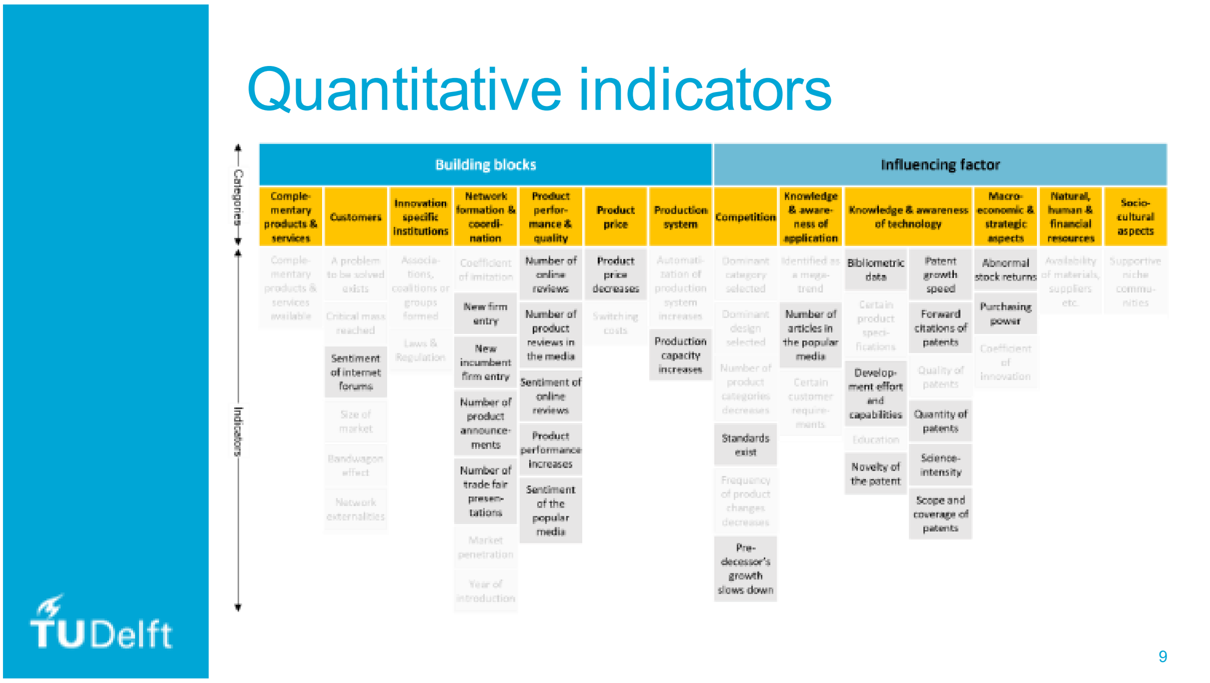


7

Quantitative indicators

	Building blocks							Influencing factor					
Categories	Complementary products & services	Customers	Innovation specific institutions	Network formation & coordination	Product performance & quality	Product price	Production system	Competition	Knowledge & awareness of application	Knowledge & awareness of technology	Macro-economic & strategic aspects	Natural, human & financial resources	Socio-cultural aspects

8


Quantitative indicators
Categories
Indicators
Building blocks
Influencing factor
Complementary products & services
Customers
Innovation specific institutions
Network formation & coordination
Product performance & quality
Product price
Production system
Competition
Knowledge & awareness of application
Knowledge & awareness of technology
Macro-economic & strategic aspects
Natural, human & financial resources
Socio-cultural aspects
Complementary products & services available
A problem to be solved exists
Critical mass reached
Sentiment of internet forums
Size of market
Bandwagon effect
Network externalities
Associations, coalitions or groups formed
Laws & Regulation
Coefficient of imitation
New firm entry
New incumbent firm entry
Number of product announcements
Number of trade fair presentations
Market penetration
Year of introduction
Number of online reviews
Number of product reviews in the media
Sentiment of online reviews
Product performance increases
Sentiment of the popular media
Product price decreases
Switching costs
Automatization of production system increases
Production capacity increases
Dominant category selected
Dominant design selected
Number of product categories decreases
Standards exist
Frequency of product changes decreases
Predecessor's growth slows down
Identified as a mega-trend
Number of articles in the popular media
Certain customer requirements
Bibliometric data
Certain product specifications
Development effort and capabilities
Education
Novelty of the patent
Patent growth speed
Forward citations of patents
Quality of patents
Quantity of patents
Science-intensity
Scope and coverage of patents
Abnormal stock returns
Purchasing power
Coefficient of innovation
Availability of materials, suppliers etc.
Supportive niche communities
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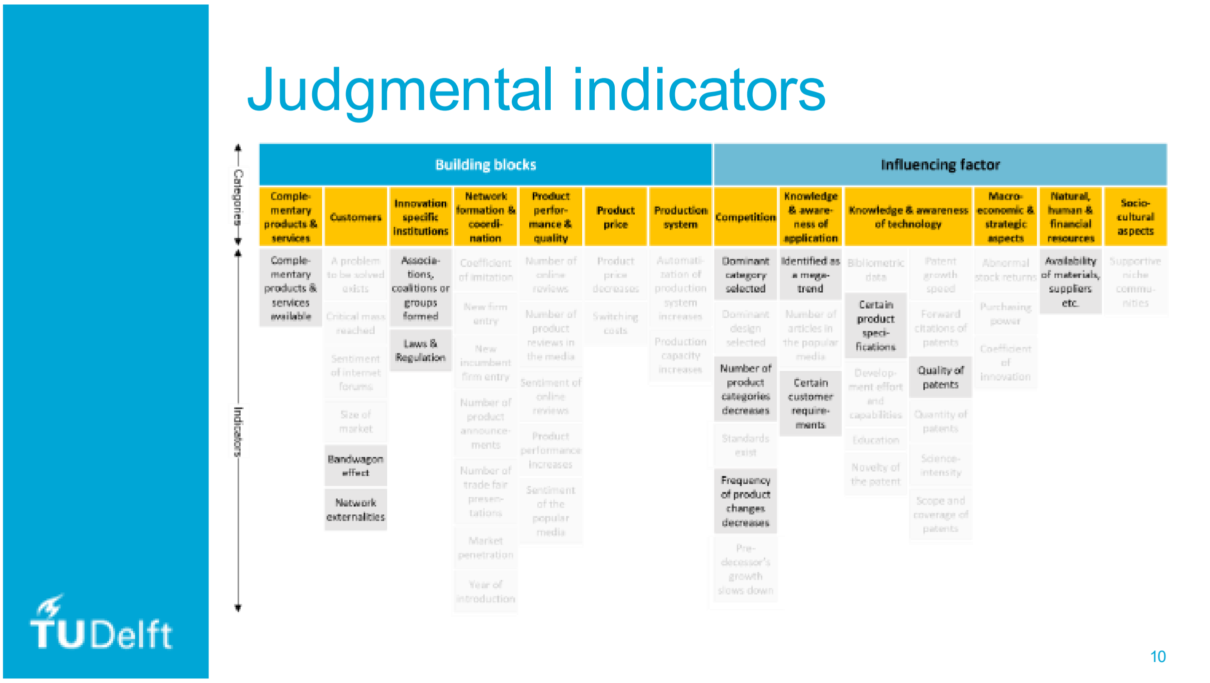
Judgmental indicators
Categories
Indicators
Building blocks
Influencing factor
Complementary products & services
Customers
Innovation specific institutions
Network formation & coordination
Product performance & quality
Product price
Production system
Competition
Knowledge & awareness of application
Knowledge & awareness of technology
Macro-economic & strategic aspects
Natural, human & financial resources
Socio-cultural aspects
Complementary products & services available
A problem to be solved exists
Critical mass reached
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Size of market
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Novelty of the patent
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Science-intensity
Scope and coverage of patents
Abnormal stock returns
Purchasing power
Coefficient of innovation
Availability of materials, suppliers etc.
Supportive niche communities
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Criteria to evaluate the indicators

Which criteria would you use to evaluate the indicators?

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Criteria to evaluate the indicators

1. Prediction
2. Timeliness of prediction
3. Availability of data
4. Cost of data
5. Quantifiable and objectivity
6. Empirical proof
7. Generalizability
8. Simplicity

Exclusion criteria

Selection criteria

Classification criteria

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Conclusion

- Do you have general remarks to the forecasting approach?
- How would you improve the concept?
- Is the forecasting approach applicable to green hydrogen?
- How can a company benefit from the forecasting approach?

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Thank you very much!

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Appendix F: Results from the validation interviews

A summary of the interview answers is provided below per candidate.

F.1 Interview candidate A

In the interview with candidate A not all questions could be answered because of an extensive discussion of the factors influencing the diffusion of green hydrogen.

Beginning

1. General information about the candidate

Information can be found in Table 15.

Page 4: Introduction

2. Do you think knowing the time point of large-scale diffusion helps researchers, companies, or government institutions? And how does it help?

It's always interesting to know the time point of large-scale diffusion. However, hydrogen is already used a lot as a feedstock. But hydrogen is not used at a moment as an energy carrier.

3. In which stage do you see green hydrogen?

It is not a new technology at all. It is only coming up because now we want to reduce our emissions and we can see that solar and winds can provide electricity at a very low cost, but only at the resource sites where you have the highest radiation or wind speeds. These locations are not close to the demand and, therefore, we need to transport the energy by converting it to hydrogen. […] We're currently in an intermediate phase.

5. Which characteristics, factors or data do you observe for the development and diffusion of green hydrogen?

Numerous factors play a role during the diffusion of green hydrogen:

- *Most dominant drivers*
    - *Electricity costs*
    - *Full-load hours in relation to CAPEX of an electrolyzer*
- *Efficiency is not important because there are hardly full load hours*
- *Development is resource-connected: Availability of solar, wind, and geothermal energy*
- *Application is driven by the market, its alternatives and its price*
- *In my view, if we are going to apply green hydrogen we have to build a new market and physical infrastructure. If this is not in place we will not use it.*
- *Hydrogen is better store and transport than electricity*
- *Cost competitiveness between the energy carriers, fuel, and heat*
- *Policies for the CO2 emission price; if there's no price for carbon, there will be no green energy or green hydrogen. It is only competitive because of subsidy.*
- *Ease of use for customers in mobility*
- *Mass production of electrolyzers will bring down the costs*

It is hard to formulate all this in one innovation indicator. It all depends on what the competition is, how we organize our energy system, and how we develop towards zero carbon.

You really have to see green hydrogen as a system, maybe it's a system innovation. But it's not one application after another. Not a lot of innovation is required for the diffusion of hydrogen. Most technologies are already there. It's about providing hydrogen at a lower cost or having a higher CO2 price in this intermediate phase.

F.2 Interview candidate B

Beginning

1. General information about the candidate

Information can be found in Table 15.

Page 4: Introduction

2. Do you think knowing the time point of large-scale diffusion helps researchers, companies, or government institutions? And how does it help?

Yes, it helps. However, if every company in the market knows the time point of large-scale diffusion investments might be postponed to a later time point delaying also the diffusion.

3. In which stage do you see green hydrogen?

I currently see green hydrogen in the market adaptation phase. The hydrogen economy is already known since 1980s and, for example, hydrogen in general is already widely used in cracking as a chemical. However, as an energy carrier or green hydrogen only niches exist.

4. Do you predict or measure the development and diffusion of green hydrogen?

Not me, but within the company colleagues do measure the development and diffusion.

5. Which characteristics, factors or data do you observe for the development and diffusion of green hydrogen?

The colleagues track the projects the company is involved with and electrolyzer prices. The CAPEX of electrolyzers is especially important as for green hydrogen the electrolyzers are not running all the time. Therefore, the CAPEX of an electrolyzer is more important than the efficiency.

Page 6: Forecasting approach – First stage

6. Are the questions in the decision tree applicable and relevant for a company or researcher?

Yes, the questions are applicable. One general remark I have is that the methods on the right, the quantitative methods, are quite naïve. Depending on what goes into the forecast, comes out of the forecast and specific patterns, depending on the underlying mathematical method, are expected. Furthermore, they are also not particularly good at forecasting revolutions. The methods on the left, the qualitative methods, are better at sudden breaks in the trend because they do not expect a standardized pattern.

Page 7: Forecasting approach – Second stage

7. What is your opinion on the hybrid approaches to overcome disadvantages of the main forecasting technique?

I think it is worthwhile. In my opinion it is easier to start with a quantitative method and then involve experts. That should give a more focused opinion.

8. Do you know alternatives to improve a forecasting technique?

No, I don't know an alternative. It is difficult.

Page 8: 13 categories

9. Do you know other building blocks or influencing factors which can predict the diffusion of green hydrogen?

For power, and also for green hydrogen, the alternatives are important. For example, if I am producing an electric vehicle and I need steel there are different alternatives. I can use eco-friendly steel made from green hydrogen but then the car would also be more expensive compared to normal steel. For a car it would be about 1000€, so it does not matter that much. But these alternatives exist for all markets of green hydrogen. There is not only one market for green hydrogen. For example, we recently had interviews with investors and they told us that green hydrogen is valuable for cosmetics. 90% of the value of cosmetics is derived from marketing. Therefore, green hydrogen adds a lot of value to the marketing strategy of cosmetics by adding a label of having green hydrogen. So basically, the alternatives to green hydrogen are important and how the niches progress through the market for the prediction of large-scale diffusion.

Page 9: Non-judgmental indicators

10. Do you have comments to any of the indicator?

For green hydrogen, the product performance is not measurable because it's a molecule. However, the efficiency of an electrolyzer could be measured.

11. Are quantitative indicators missing?

As already mentioned, an indicator for the alternatives is missing.

Page 10: Judgmental indicators

12. Do you have comments to any of the indicator?

No.

13. Are any judgmental indicators missing?

For green hydrogen we also must take into account the hype. 10 years ago, it was a hot air balloon. But now it becomes more real. I also think for some companies, green hydrogen is not fully supported by the higher management because it is too risky. The lower management might stand behind it, but the higher management might not believe in it.

14. Do you agree with the initial assumption that the indicators can predict the start of large-scale diffusion?

In principle, I agree with the assumption. However, the context is important and needs to be more emphasized. Green hydrogen brings flexibility, but it could also be a marketing thing. Sometimes it actually makes sense, and sometimes green hydrogen just does not make sense yet. Green hydrogen might start as a niche until it gets more credible and more accepted. And then it might replace steam reforming and maybe later natural gas.

Page 11: Criteria

15. Which information is relevant to know about an indicator? Which criteria would you use to evaluate the indicators?

I am not sure.

Page 12: Criteria

16. Are criteria missing?

No. However, I would like to emphasize the simplicity of the indicators. Even if you have a very complicated model, it should be explainable. Other should understand why such a forecast has been made.

Page 13: Conclusion

17. Do you have general remarks to the forecasting approach?

See next question.

18. How would you improve the concept?

Green hydrogen should be seen on levels, representing different niche applications. Each of this level is depended on the context. This should be more emphasized. For green hydrogen as an energy carrier there are two opportunities: first with a budget electrolyzer if too much energy is in the grid and secondly with a very efficient electrolyzer connected to an offshore wind farm. For both applications different electrolyzers are needed.

Furthermore, you could also combine your forecasting approach with a modelling approach to compare different results based on conditions or assumptions.

19. Is the forecasting approach applicable to green hydrogen?

In our company, we also do kind of a forecast to see when, which hydrogen application will be usable. The analysis is based upon alternatives and there it is important to not only have a qualitative approach but also quantitative approach to compare the alternatives better.

20. How can a company benefit from the forecasting approach?

The forecast we do in our company brings a lot of discussion with it among the experts because of different views.

F.3 Interview candidate C

Beginning

1. General information about the candidate

Information can be found in Table 15.

Page 4: Introduction

2. Do you think knowing the time point of large-scale diffusion helps researchers, companies, or government institutions? And how does it help?

Absolutely, if you can come up with specific indicators and values that play an important role when a technology or product will enter into a mass market environment it would be helpful. It also becomes *interesting to now step into the technology and invest in it. But it is good to know if the indicators are validated and what's the predictive value for it.*

3. In which stage do you see green hydrogen?

I see green hydrogen in the early market adaptation phase because of the prices for the technology itself and the price difference to gray and blue hydrogen. Maybe I would see it between early and late market adaptation phase because we know about the technology, there are plans about gigawatt electrolyzer facilities, but we are struggling to some extent where to place it: here in Netherlands, where it wouldn't be subsidized anymore, or where the electricity is even cheaper. The whole value chain for green hydrogen is not in place and all this should be in place before we go into the mass market.

4. Do you predict or measure the development and diffusion of green hydrogen?

No, we do not measure or predict it. So, we actually lack the tooling to do so. But we understand now that this is the time to start investing for hydrogen in mobility, single side solutions, decentralized solutions, but also hydrogen as a mass energy carrier through pipeline systems. From a [large energy corporation] perspective, we were a laggard in this area because we have been neglecting hydrogen for a long time now. We now see that we have to speed up activities and get to know the technology to position ourselves

5. Which characteristics, factors or data do you observe for the development and diffusion of green hydrogen?

The CAPEX for the electrolyzer technology. Additionally, we are also looking for the take-off market where it is logical that hydrogen can play an important role. Will this already be in a mass market or a niche market like a single side solution. But the price is a very important factor, and it is seen in comparison to fossil and relative to the CO2 pricing.

Page 6: Forecasting approach – First stage

6. Are the questions in the decision tree applicable and relevant for a company or researcher?

Yes, it is applicable.

Page 7: Forecasting approach – Second stage

7. What is your opinion on the hybrid approaches to overcome disadvantages of the main forecasting technique?

Back in the times when I was working as a management consultant most companies wanted to know how successful their business development program is? And we came in and showed them insights where they can grow. We basically did two things, which you also show here. First, we were data-driven and looked at data and information. But we always combined it with industry experts, and let them judge our ideas, and collect their thoughts and opinions. This was the most relevant work to our clients. So, I do think it is always a good thing to use a hybrid approach.

8. Do you know alternatives to improve a forecasting technique?

I do not know another method.

Page 8: 13 categories

9. Do you know other building blocks or influencing factors which can predict the diffusion of green hydrogen?

Maybe the sustainability impact of the technology should be covered by one of the indicators. Has the sustainability impact been talked about? Has it been measured or calculated? I think this is relevant. Because one of the things we see is that if we product hydrogen from grey electricity the societal discussion would start, and disputes would arise. Are we going to waste our precious electricity to convert it to green hydrogen? That is a discussion which is taking place for years already. Basically, I would like to see a stronger emphasis on the societal aspects.

Page 9: Non-judgmental indicators

10. Do you have comments to any of the indicator?

The indicator New incumbent firm entry is an important indicator. At the beginning we were struggling a lot with green hydrogen, so we cooperated with Siemens and other energy companies. And now all the sudden a big grey hydrogen producer enters the market.

The price of green hydrogen always has to be seen in comparison to the market alternatives. Because also the other benefits of green hydrogen (it's not polluting, no CO2, noiseless) are always seen in comparison. Maybe it has something to do with the acceptance of overall benefits. If you still have to explain a lot about the benefits of green hydrogen, there is no acceptance whatsoever. And if all of a sudden companies or people start to understand the benefits and appreciate the benefits, then you are also a step further. It is about the perceived benefits of customers. Five years ago, nobody wanted green hydrogen. But now, you see decentralized power production facilities, which do not stink, do not make noise, and do not pollute and customers are interested. We are now in a different area of deployment.

I also think that public news are important because now you can also see not only experts talking about green hydrogen in the daily news but also the mass market is joining.

11. Are quantitative indicators missing?

No.

Page 10: Judgmental indicators

12. Do you have comments to any of the indicator?

The standards are important to ensure that everybody can work with the technology.

13. Are any judgmental indicators missing?

No, it looks good.

Page 11: Criteria

15. Which information is relevant to know about an indicator? Which criteria would you use to evaluate the indicators?

It is important to have robust data for the indicator. And also the robustness of the indicator is important.

Page 12: Criteria

16. Are criteria missing?

No, I think this is okay.

Page 13: Conclusion

17. Do you have general remarks to the forecasting approach?

I think it is a good effort, a valuable effort and I am impressed about what you do.

18. How would you improve the concept?

I think the only thing that makes it more robust and acceptable is that you test your forecasting approach on different technologies and compare it to a historical analysis. That is probably too much to carry out for you. But that would really be valuable because otherwise it will be stored next to other assessment tools.

20. How can a company benefit from the forecasting approach?

This research would really be relevant for our strategy department because it is a good tooling which might be helpful for us.

F.4 Interview candidate D

Beginning

1. General information about the candidate

Information can be found in Table 15.

Page 4: Introduction

2. Do you think knowing the time point of large-scale diffusion helps researchers, companies, or government institutions? And how does it help?

Rather than knowing the actual timepoint of diffusion I would like to know what triggers the diffusion and on what it depends on.

3. In which stage do you see green hydrogen?

I see green hydrogen in early market adaption phase because there is still a lot of research needed. It is definitely not in the large-scale diffusion phase.

4. Do you predict or measure the development and diffusion of green hydrogen?

Not yet, but we are doing a project where we try to find out the status of different technologies in the energy chain from hydrogen production to hydrogen fueling, compromising the distribution, transportation, and storage.

5. Which characteristics, factors or data do you observe for the development and diffusion of green hydrogen?

The current efficiency factor and theoretical efficiency factor is relevant for us. What is the gap between the practice and theory? And what does the scale mean, does it have the same efficiency if it is a small-scale compared to a large-scale application.

Page 7: Forecasting approach – Second stage

7. What is your opinion on the hybrid approaches to overcome disadvantages of the main forecasting technique?

On a very simple level, I think its always good to combine judgement with quantitative data. Judgements can be very biased if for example somebody is in favor of battery technology or hydrogen or if somebody does not the see the whole chain including storing and also transporting hydrogen. In this case you cannot only take the efficiency of hydrogen into account but also the transportation.

8. Do you know alternatives to improve a forecasting technique?

No. We work less methodological but more by looking at the literature and finding out if the literature is good. But generally, I would say it is always good to combine judgmental and quantitative indicators.

Page 8: 13 categories

9. Do you know other building blocks or influencing factors which can predict the diffusion of green hydrogen?

By just looking at the categories, I am missing something for market creation. You need to create a demand because the customers will not demand it by themselves. It is radically new, so you need a technology push. Furthermore, I am missing the actors. I would like to know who is influencing what.

Page 9: Non-judgmental indicators

10. Do you have comments to any of the indicator?

No.

11. Are quantitative indicators missing?

I miss again the market creation. The market alone is not sufficient to create demand.

Page 10: Judgmental indicators

12. Do you have comments to any of the indicator?

Laws & Regulations are very important for hydrogen in cars. If a government sets a target for hydrogen in cars it is also their obligation to fulfill. But the market alone is not sufficient to create the demand.

From my perspective, I would place Network Externalities under Laws & Regulation and not under customer. Network Externalities are something for governments to arrange to make sure that there is a network because the market will not create it on its own.

13. Are any judgmental indicators missing?

I think it also matters how easy something is to use. If everything is adapted more people would choose that option.

14. Do you agree with the initial assumption that the indicators can predict the start of large-scale diffusion?

No, I do not think that it will be enough that the indicators will predict the moment in time when an innovation enters the mass market. For me large-scale diffusion depends on the alternatives. It is not only about the indicators. In the end it comes down to good value for money and if the alternative offers a better network, less time for charging or fueling, more car brands then you would go for the alternative. What also matters is what your peers do. Will they be part of the movement then you would also like to join.

The alternatives are my doubt, but it is not a big doubt. The question is if people are always rationally thinking. Will people really switch if it is the better product for a cheaper price?

Page 11: Criteria

15. Which information is relevant to know about an indicator? Which criteria would you use to evaluate the indicators?

Reliability of the indicators would be important for me.

Page 12: Criteria

16. Are criteria missing?

What I also would like to check is if the indicators overlap. You have around 40 indicators and they might indicate the same.

Page 13: Conclusion

17. Do you have general remarks to the forecasting approach?

I would suggest that you should test this forecasting approach. Take a historical example, try the model, and see if the forecast of the model is correct.

19. How would you improve the concept?

I would say that this forecasting approach is the first step, and you should add other building blocks to improve it.

20. Is the forecasting approach applicable to green hydrogen?

You now took one technology. I would say that you should also take the alternatives of green hydrogen into account.

21. How can a government benefit from the forecasting approach?

If you could point on the decisive indicators, the game changer, that would be really useful.