USING TREND RECOGNITION TO IMPROVE INNOVATION PORTFOLIO MANAGEMENT

Lappeenrannan–Lahden teknillinen yliopisto LUT

Tuotantotalouden kandidaatintyö

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Trendien tunnistaminen innovaatioportfolion hallinnan työkaluna

Tuotantotalouden kandidaatintyö

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51 sivua, 10 kuvaa, 3 taulukkoa ja 0 liitettä

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Tämä kandidaatintyö pyrkii tutkimaan, miten innovaatioportfolion hallintaa voisi kehittää trendien tunnistamisen avulla. Työ pyrkii löytämään synergioita kahden alan väliltä: data-analytiikan ja innovaatiojohtamisen. Trendien tunnistamista käsitellään sosiaalisen median analytiikan kautta ja keskittyminen ohjataan näin kuluttajatrendeihin. Työ on toteutettu kirjallisuuskatsauksena ja työn lähteinä on käytetty tieteellisiä artikkeleita sekä muita aiheeseen relevantteja julkaisuja.

Innovaatioportfolion hallinnan rooli on tuottaa organisaatiolle innovaatioita, joita voidaan viedä tuotekehitykseen ja lopulta kaupallistaa. Tämä on yrityksen selviytymisen sekä taloudellisen menestymisen kannalta olennaista. Trendien tunnistaminen puolestaan viittaa tässä työssä kuluttajatrendien analysoimiseen sosiaalisen median datasta. Siinä pyrkimys on havaita alkavia organisaation kohderyhmiä koskettavia trendejä, joilla on kaupallista arvoa organisaatioille. Trendien tunnistaminen innovaatioportfolion hallinnan työkaluna auttaa organisaatioita kehittämään innovaatioita, jotka hyötyvät alkavista kuluttajatrendeistä. Trendien tunnistaminen luo arvoa, sillä innovaatioiden diffuusion alku on hidas ja taloudellinen potentiaali alkaa realisoitumaan vasta myöhemmissä vaiheissa.

Trendien tunnistaminen innovaatioportfolion hallinnan työkaluna antaa organisaatioille mahdollisuuden kuunnella kuluttajia kustannustehokkaalla ja skaalautuvalla tavalla. Tämä luo kiinnostavan vaihtoehdon perinteisemmille metodeille, jotka ovat perustuneet haastatteluihin ja kyselyihin. Tämä auttaa myös datan laadussa, sillä kuluttajat antavat tietoa sosiaalisen median kautta ilman organisaatioiden häirintää.

ABSTRACT

Lappeenranta–Lahti University of Technology LUT

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Industrial Engineering and Management

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Using trend recognition to improve innovation portfolio management

Bachelor's thesis

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51 pages, 10 figures, 3 tables, and 0 appendices

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Keywords: innovation portfolio, innovation portfolio management, trend recognition, trend-spotting, innovation management, data analytics, social media analytics, fuzzy front-end

The bachelor's thesis researches how innovation portfolio management could be improved with trend recognition. The thesis aims to find synergies between two fields: data analytics and innovation management. In the thesis, trend recognition is done through social media analytics, and the thesis will thus focus on consumer trends. The thesis is done through a literature review and scientific articles and other relevant publications have been used as the sources.

The role of innovation portfolio management is to produce innovation that can be carried into further development and eventually monetized. This is crucial for the organization's longevity and financial success. Trend recognition in this thesis refers to analyzing consumer trends through social media data. It aims to recognize emerging trends that touch the organization's target audience and that have commercial value. The utilization of trend recognition in innovation portfolio management helps organizations to create innovations that benefit from the underlying consumer trends. Trend recognition brings value because the diffusion of innovation starts slow, and the commercial potential starts to realize during later phases.

Trend recognition in innovation portfolio management enables organizations to hear the voice of the customer in a cost-efficient and scalable way. This brings an attractive option to the more traditional methods which have based on surveys and interviews. This will also increase the quality of data because consumers release information through social media without corporate interference.

SYMBOLS AND ABBREVIATIONS

Abbreviations

IPM	innovation portfolio management
SMA	social media analytics
VOC	voice of the customer
VOP	voice of the product
B2B	business-to-business
B2C	business-to-consumer
NPL	natural language processing
ML	machine learning
AI	artificial intelligence
R&D	research and development
TRL	technology readiness levels
ROM	rough order of magnitude
FFTD	fast and frugal decision tree
DFA	dynamic factory analysis
ENPV	expected net present value

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1 Introduction

1.1 Background of the thesis

Data analytics is being used widely in business to improve the performance of organizations. Data analytics and big data are used in such large amounts that they shouldn't be considered as emerging innovations anymore (Blackburn, Alexander et al. 2017). The usage of data analytics in business has grown significantly throughout the years (Statista 2022d), which indicates that data-driven processes seem to bring added value to organizations. Also, digital platforms have enabled the discovery and collection of great amounts of data, which wasn't available before these platforms arose (Nuccio, Guerzoni 2019, Du, Kamakura 2012).

Even though data analytics is being used widely in business decisions, there's a lack of scientific literature on the usage of data analytics to support decisions taken in innovation portfolio management, despite their critical importance to sustained performance of the firm (Cooper, Robert, Edgett et al. 2001). The innovation portfolio management (IPM) process is important for many organizations, but it has seen a lack of evolution while the corporate playing field has seen major changes. New business models have emerged, consumer behavior has changed, and a plethora of digital tools have become readily available. When businesses have encountered such change, one might ask "are some IPM methods partially outdated?". There is a lot of academic literature on the shortcomings of current IPM methods (Archer, Ghasemzadeh 1999, Qingrui, Xiaoqing et al. 2000, Artto, Martinsuo et al. 2001, Cooper, Robert G., Edgett et al. 2004, Klingebiel, Rammer 2014). This sparked a need to research new ways to improve IPM in the modern world.

Inspired by these findings, I conducted a literature review to explore existing solutions of data analytics in IPM to understand, how data – and especially trend recognition – could be utilized in IPM to improve business performance.

1.2 Findings

The research of the thesis found that trend analysis opens up many possibilities for IPM. According to the research, recognizing consumer trends can bring substantial value to organizations in more than one way. It seems that trend analysis helps to solve some classic IPM problems regarding the lack of information and the quality of the information. Also, recognizing consumer trends has an exciting value proposition for building a competitive advantage in the long term. According to the research, trend recognition seems to be a viable option for trend forecasting, which is an extremely challenging task.

The research also found that there are many possibilities for utilizing consumer trend knowledge. What is important, however, is how the analytic process will be integrated into IPM. That is why the thesis provides a framework that innovation managers can utilize to successfully integrate consumer trend recognition into their innovation process.

1.3 The purpose of the thesis and research questions

The purpose of the thesis is to better understand how data analytics is being used in business and to get valuable insights on how data analytics and especially trend recognition can be integrated into IPM.

The main research question of the thesis is: **How innovation portfolio management could be improved with trend recognition?**

The thesis will approach this question with a set of sub-questions to split the problem into more manageable segments. These sub-questions are:

- How to recognize trends through data analytics?
- Where the relevant data can be found?
- How the trend analysis should be used in IPM?
- What value trend analysis could offer to IPM?

1.4 Limitations

Both data analytics and innovation portfolio management contain vast amounts of information, theories, and challenges. The usage of data analytics in IPM is a broad topic, which is why the thesis focuses on a very specific niche inside it. Here are the main limitations of the thesis:

1. The thesis focuses on how IPM could be improved with consumer trend recognition, and it will not research other methods of improving IPM, even though it seems that there are other ways of improving the innovation management process (Gordon, Tarafdar et al. 2008, Lawson, Krause et al. 2015, Kim, Choi et al. 2019, Truong, Papagiannidis 2022, Bhimani, Mention et al. 2019, Dou 2004, Veugelers, Bury et al. 2010).

2. The thesis focuses on data that gives insights into consumer trends thus it doesn't research, for example, trends that are related to a B2B environment.

3. The thesis will focus on recognizing consumer trends rather than predicting them. Trend prediction or trend forecasting is such a difficult topic itself, that it should be a topic for its own study.

4. The source of the data will be social media, which is why the thesis will focus on social media analytics (SMA). The thesis will not dive deep into other sources of data, even though there might be other good options for companies as well.

5. The thesis does not seek to develop a new data analytics method but focuses on the challenge of integrating trend recognition into IPM.

By limiting my thesis, the thesis hopes to gain a deeper understanding of certain aspects of using data analytics in IPM and hopefully provide valuable insights on how trend recognition might improve the innovation process.

1.5 Structure

The thesis is researching two separate fields, data analytics, and IPM, and trying to find synergies between them. Because of this, the thesis has four main parts in addition to the introduction and conclusions chapters. The thesis will first introduce these two fields to build a thorough enough understanding of both fields, then bind them together in order to research possibilities for integration and value-creation. Even though the thesis goes through the theory of data analytics, the emphasis will remain on IPM.

First, the thesis goes through the relevant theory of data analytics and trend recognition, and the value that they offer to businesses. Second, the thesis goes through the theory regarding innovation portfolio and IPM to understand the nuances of managing innovations. Third, research on how these two fields could be integrated is conducted and multiple possibilities for integration are provided. Fourth and final, the thesis goes through why and how the integration might bring value to IPM.

2 Data analytics in trend recognition

Digital platforms enable the collection of data. Countless interactions are made daily which means that a great amount of data is formed as well. Large amounts of data make it possible to recognize patterns that organizations can monetize (Blackburn, Alexander et al. 2017). Consumer trends are one example of these patterns.

2.1 What is data?

The term data refers to a set of unorganized information that has been purposely gathered to gain meaningful insights. This information can be facts, events, things, ideas and much more. For example, a set of data could consist of mortality rate (facts), home ownership (things), or political beliefs (ideas). (Aneshensel 2016.)

By itself, data is meaningless. It is just a collection of information represented by corresponding symbols (Aneshensel 2016). This means that data must be interpreted. Even though data consist of information that is objective by definition, it has some very subjective qualities – it has to be observed and interpreted by someone to give it meaning. Thus, data can mean different things depending on who is interpreting it.

Regarding this notion of subjectivity, data can be split into three main categories: primary, secondary, and tertiary. Primary data is generated by someone, who is interpreting the data. Secondary data is raw data that is collected by someone else. Finally, tertiary data has been analyzed by the primary or secondary user. All of the categories have advantages and disadvantages. The more you can affect how data is collected the more you have control over it, but the more time and resources it takes. Also, it is good to recognize that data might have some prejudice, and using data collected or analyzed by others might make the data unpredictable or less reliable. (Blaikie 2003.)

Nowadays data that corporations collect and utilize is being created in such vast quantities that it is often called *big data*. Big data is most often described with the framework of three V's: volume, velocity, and variety (Chen, Chiang et al. 2012). These three factors separate big data from just "data". Volume refers to the great amount of data, velocity refers to the high speed that new data is being produced, and variety refers to the high variability in the structure of a dataset (Gandomi, Haider 2015). Other challenges have been suggested as well, a common one being the four V's with the fourth one being veracity, the truthfulness of the data (Stieglitz, Mirbabaie et al. 2018).

Big data can be split into structured and unstructured data. Structured data makes up only a small minority of all data and it refers to the tabular data that is stored in spreadsheets and relational databases. Unstructured data often lacks the structural order that machines require for analysis. Unstructured data can be, among other things, text, images, audio, or video. (Gandomi, Haider 2015.) Unstructured data will be the most relevant type of data for trend recognition. This is because trend recognition requires information on sentiment, which can be gathered from various social media platforms that have unconstructed data (Rambocas, Pacheco 2018).

The type of data that is collected to make sufficient insights about consumer trends will most likely fulfill the aforementioned characteristics of "big data". For this reason, it will not be necessary to make a distinction between data and big data in this thesis. Thus, the thesis will use the term "data" or "data analytics", but more often than not referring to big data and big data analytics. Also, big data comes with lots of possibilities and problems relating to the three V's, and plenty of technologies, methods, and tools. These are all important factors to understand when utilizing big data, but they are outside the scope of this thesis.

2.2 Recognizing trends through data analysis

Because data doesn't have intrinsic meaning, its nature must be interpreted. The understanding of the data can be achieved through data analysis. Data analysis is the systematic process where one organizes information into intelligible patterns. (Aneshensel 2016.) Simply, it tries to make sense of a set of unorganized information. Ideally, these insights can be used in real life to bring value to, among many other things, business.

The process of analyzing big data can be broken into two processes. data management and analytics. These processes can be broken into smaller steps, as shown in fig. 1. During data management the data is collected, prepared, and stored for analysis. During analytics valuable insights are acquired for decision-making. (Gandomi, Haider 2015.)

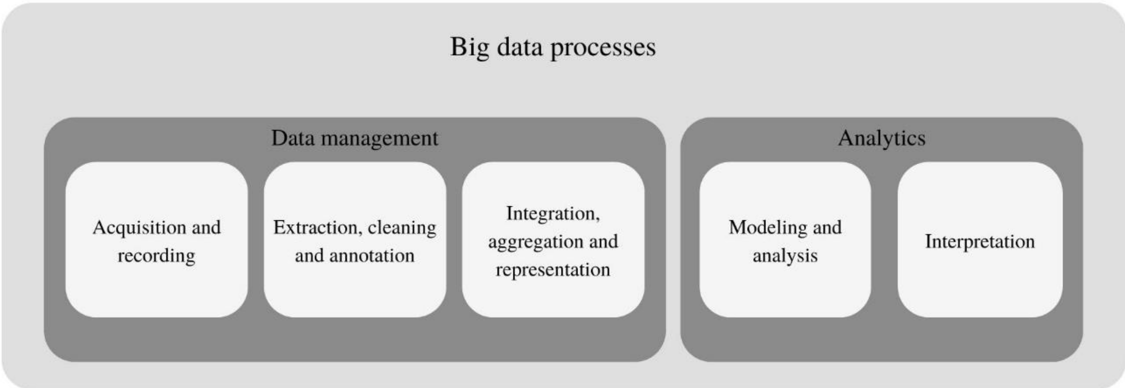

Figure 1: The process of analyzing data after Gandomi and Haider (2015)

Depending on the type of data, different techniques should be used to analyze the data effectively. Gandomi and Haider (2015) divided these techniques into five subsets, from which three are relevant to the research question of this thesis: text analytics, predictive analytics, and social media analytics. Text analytics refers to extracting information from textual data, such as blogs, social network feeds, and online forums, among others. Predictive analytics refers to the different methods that predict future outcomes by finding patterns and relationships from historical data. Finally, social media analytics refers to the analysis of data from social platforms. The data from social media is user generated (Du, Netzer et al. 2021). These three techniques will have some overlap in the context of trend recognition, because the data collected from social media includes textual data, and emerging patterns are being analyzed.

Data analytics allows us to recognize emerging patterns from historical and current data. When using social media data as the dataset, it allows us to recognize or forecast consumer trends (Rambocas, Pacheco 2018). In the thesis, the emphasis is on trend recognition, not on trend forecasting. Recognition refers to a reactive approach whereas forecasting refers to a proactive one. Trend recognition, which is often referred to as “trendspotting”, has been studied in the academic literature and its value in many business fields has been noticed

(Andreassen, Lervik-Olsen et al. 2015, Du, Kamakura 2012, Du, Netzer et al. 2021, Salzman 2017). These references research the utilization of consumer trends, but probably the most recognized usage of trend analysis comes from the financial sector where it's utilized in technical analysis (Masteika, Rutkauskas 2012, Thomsett 2019, Han, Peng et al. 2020). However, these trends often refer to the movements and patterns of stock prices (Masteika, Rutkauskas 2012) and should not be confused with consumer trends which are the topic of this thesis.

Trend recognition allows organizations to produce innovations that are valuable to consumers more consistently. It also aids in detecting new opportunities and works as a facilitator for ideas which can both help in producing more disruptive innovations. This can be very beneficial because while marginal innovations offer marginal improvements, radical innovations enable radical improvements in the organization's profits. (Andreassen, Lervik-Olsen et al. 2015.) It is no wonder that trend recognition has already become an important tool for marketing intelligence for analyzing consumer behavior (Du, Kamakura 2012). Marketing intelligence relied heavily on qualitative trendspotting before the mass adoption of social media platforms, which relied heavily on a small set of trendsetters or opinion leaders (Du, Kamakura 2012). However, social media platforms create such vast amounts of consumer data, that they enable quantitative trendspotting and the usage of more advanced analysis models like the ones provided earlier. In addition to the earlier mentioned data analysis methods provided by Gandomi and Haider (2015), Du and Kamakura (2012) suggest that dynamic factory analysis (DFA), which is derived from factory analysis, has been long used in identifying common trend lines in many fields, such as econometrics, psychometrics, environmetrics, and statistics and that it offers value to marketing intelligence as well. The widespread utilization of this method indicates that DFA could be also utilized in trend analysis regarding IPM.

Data analytics seems to be very suitable for effective trend recognition. As said earlier, data that is relevant to trend recognition can be gathered from several places – one of the most obvious ones being social media. That is why the thesis will focus on social media as the main source of data.

2.3 Social media analytics

Many enterprises treat social media like a promotional tool – a one-way communication platform. However, the unique aspect of social media in contrast to traditional promotional media is that it allows for two-way communication between the enterprise and stakeholders. Social media can act as a window to customers' minds. (Moe, Schweidel 2017.) With SMA our mission is to look through this window with as much clarity as possible.

SMA refers to collecting and analyzing data from social media platforms. The popularity of SMA has risen drastically after many platforms allowed organizations to access the large amount of consumer data that these platforms gather on daily basis (Lee 2018). The number of social media users has risen from 2,73 billion in 2017 to an estimated 4,59 billion in 2022 (Statista 2022b). That means an over 9 percent CAGR. Also, according to Statista (2022b), this amount is forecasted to grow to 5,85 billion in 2027, as shown in fig. 2. SMA is a great source of consumer insights for enterprises because the various platforms capture such vast amounts of beliefs and opinions shared by active users. In other words, social media allows organizations to hear the voice of the customer or VOC (Moe, Schweidel 2017). Also, the platforms often offer possibilities for automatic analysis via built-in tools, third-party solutions, or APIs which make SMA increasingly attainable for enterprises of all sizes.

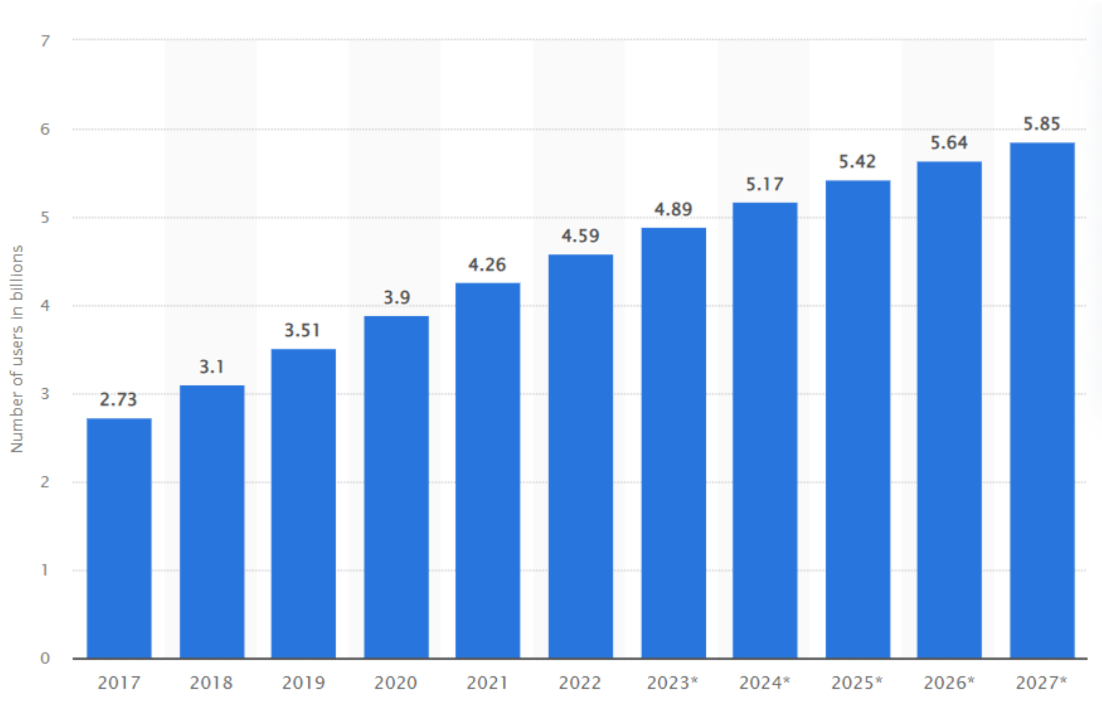

Figure 2: Number of social media users (Statista 2022b)

There is a myriad of social media platforms that are built around different themes and focus on different ways of engaging. Some of the most popular platforms include:

- YouTube, which is used in sharing videos around various topics,
- Twitter, which is a micro-blog platform that allows sharing in text format,
- Instagram, which is mostly used for sharing pictures or short videos,
- TikTok, which is a fast-growing platform for sharing short videos,
- LinkedIn, which is a professional social platform,
- Reddit, which allows the creation of sub-pages or communities around various topics,
- and Facebook, which has around 2,93 billion monthly active users (Statista 2022a) that share text, images, videos, and links to their connections.

These platforms enable enterprises to collect data in text, picture, audio, or video format. According to Lee (2018), depending on the enterprise's market orientation, SMA can be applied to either the customer or competitor. These can be categorized further into real-time and non-real-time. Real-time activities revolve around observant and reactive measures, whereas non-real-time activities are more proactive, strategic, and high-level. Refer to table. 1 for a more in-depth breakdown of the different functions of these activities.

Table 1: A typology of enterprise SMA after Lee (2018)

		Timelines	
		Real-time	Non-real-time
Market orientation	Customer	Real-time customer SMA Reactive marketng efforts • keyword analysis • location analysis • conversation analysis • complaint detection • alerts from online reviews and comments	Non-real-time customer SMA Proactive marketng efforts • identification of profitable customer groups • social network analysis • influencer analysis • web analytics • sentiment analysis
	Competitor	Real-time competitive SMA Operational intelligence • monitoring of prices and promotions • news alert • headlines • new product announcements • mergers and acquisitions	Non-real-time competitive SMA Strategic and tactical intelligence • periodic trend analysis of competitors' pricing • new product development • technology development • customer services • complaints • employee comments

There are many SMA methods, but the most widely used ones are sentiment analysis, social network analysis, statistical analysis, and image/video analysis, which are still in an earlier stage of development (Lee 2018).

Sentiment analysis or opinion mining utilizes Natural Language Processing (NLP) to extract and interpret opinions from text and classify them into positive, negative, or neutral sentiments. The two main ways of doing this are machine learning and a lexicon-based approach. Machine learning uses algorithms while the lexicon-based approach uses a dictionary to rank different texts into negative, positive, or neutral sentiments. The lexicon-based approach has some limitations because natural language can be too complex. The machine learning method has more potential but requires large amounts of training data for good classification accuracy. (Drus, Khalid 2019.) However, one must be aware of sampling bias in the data when conducting sentiment analysis – for example, a small unsatisfied minority can be much more vocal on social media which might skew the results of the analysis (Fan, Gordon 2014).

Statistical analysis uses mathematical models, such as the Monte Carlo method, regression models, factor analysis, and cluster analysis for advanced analytics. Usually, these methods require the transformation of the original content into a coded format. (Lee 2018.) Trend analysis is based on statistical methods, such as time-series analysis and regression analysis (Drus, Khalid 2019) thus this method is important in the context of trend recognition and forecasting. This is because even if we are able to recognize trends using other methods, we have to make an estimation of the strength or the future outlook of the trend – not every trend is meaningful or long-term. Statistical analysis can help with this estimation part of analyzing trends.

Social network analysis is based on social network theory and analyzes the structures of social networks. This type of analysis can be used, for example, in identifying influencers to target in marketing. (Lee 2018.) Tools and techniques developed for social network analysis and the mining of social networks could provide significant value to trend recognition, for example through social CRM, which could help in anticipating customers' needs, future business opportunities, and reputation monitoring (Bonchi, Castillo et al. 2011).

Image and video analysis are still in the earlier stages of development, but they are very important for trend recognition going forward due to the popularity of these types of media on web 2.0. For example, image analysis can offer information about fashion trends or locational information on people (Lee 2018). Technologies such as ML or AI are important in the development of these analyzing methods.

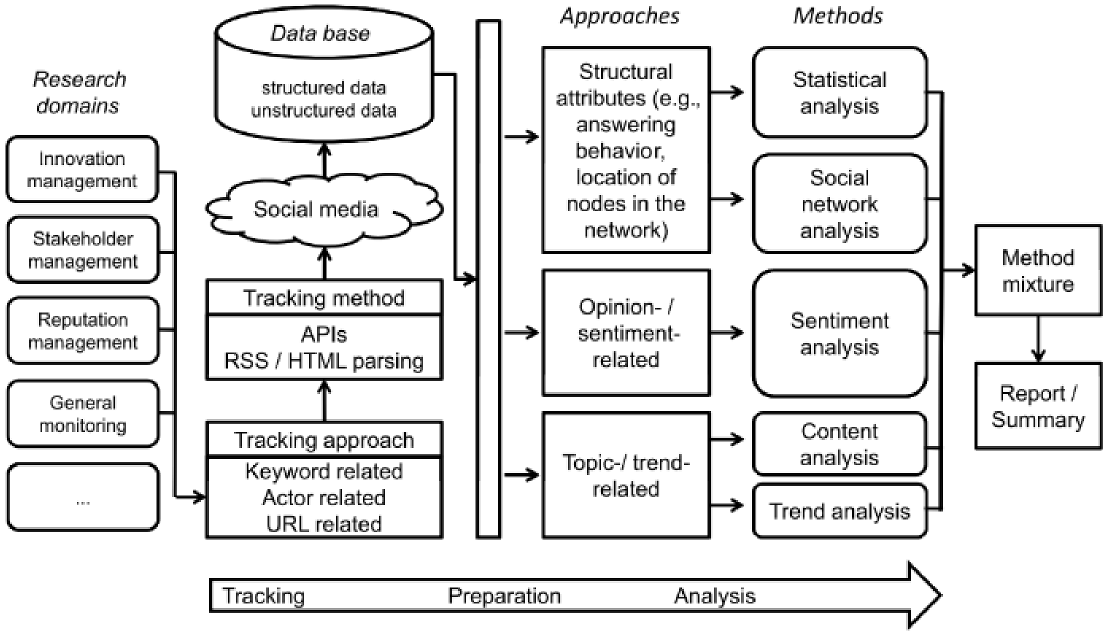

Figure 3: SMA process (Stieglitz, Dang-Xuan et al. 2014)

Fig. 3 shows the process of SMA. The analysis is done for some research domain, in the context of the thesis, it would be innovation management. Data is tracked and collected into a database. Then it is analyzed with a certain approach, for example with trend recognition it would be sentiment-related or trend-related. Finally, the analysis is done through different methods which were discussed earlier in this chapter. During every phase, important decisions are being made, like what variables should be tracked and how, what is the approach for the analysis, and what are the most suitable methods to analyze the data.

SMA faces challenges that will naturally affect the usage of SMA and trend analysis in IPM. SMA is an interdisciplinary field, so the data is being analyzed by researchers with diverse backgrounds. Each discipline has its own tradition, competencies, and prejudices. Event and topic detection rises as another challenge due to the large volume of data. In response to this, topic discovery and event detection algorithms have been developed. The volume and velocity of the data force researchers to stress the importance of suitable software architecture. Also, the variety – or the unstructured nature – creates a challenge for data visualization and the veracity of the data rises uncertainty about the quality of the data. (Stieglitz, Mirbabaie et al. 2018.) All these challenges relate to the common challenges of big data, the four V's mentioned earlier in the thesis.

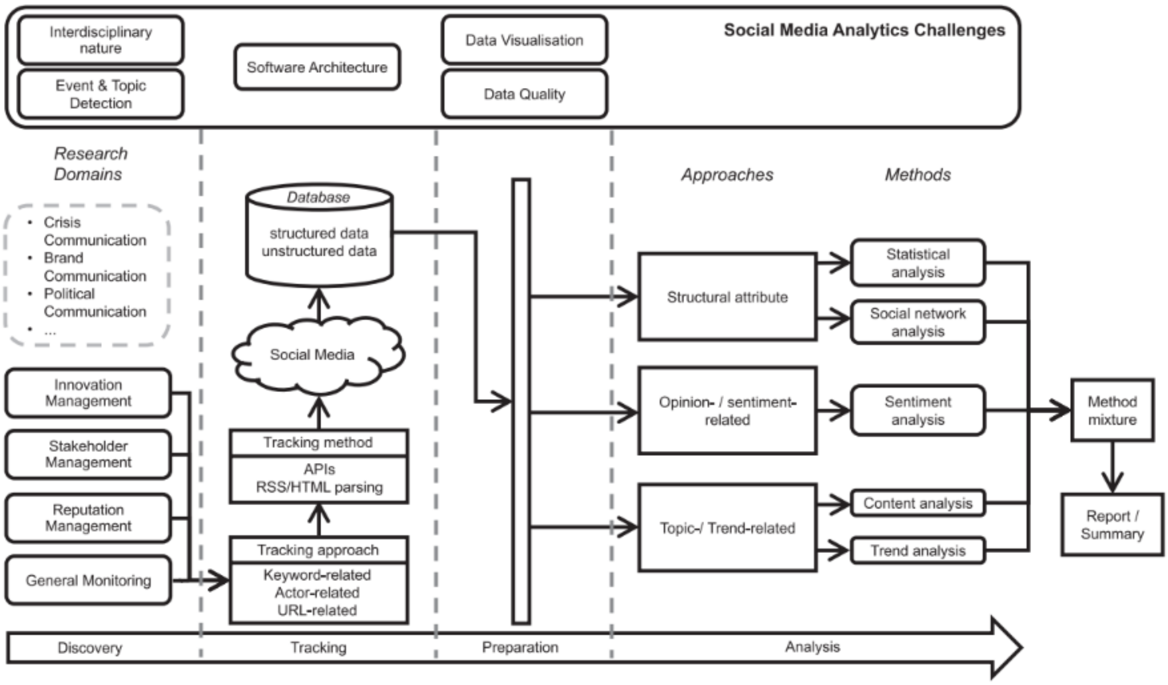

Figure 4: Challenges of SMA (Stieglitz, Mirbabaie et al. 2018)

Above in fig. 4, the aforementioned problems are connected to the phases of the SMA process. As can be seen, the discovery, tracking, and preparation of data have multiple challenges even before the actual analysis begins.

2.4 Value of data-driven business management

High-performing companies utilize data analytics much more than low-performing companies. There is a growing demand and pressure for justifying business decisions with data instead of experience. (Hopkins, LaValle et al. 2011.) This indicates that using data analytics enhances business performance and brings value to business processes. Underneath in fig. 5 is a comparison of top-performing and lower-performing enterprises in their usage of data analytics. The usage of analytics has been split into 11 different business processes. The figure shows that across all the activities, high-performing enterprises rely much more on analytics than lower performers. A likelihood of 1.0 indicated that an organization is equally likely to use intuition and analytics. Regarding R&D, which is somewhat comparable to IPM, top performers seem to rely quite strongly on analytics, whereas lower performers tend to lean towards intuition – or gut feeling. This indicates that data analytics has a prominent place in IPM.

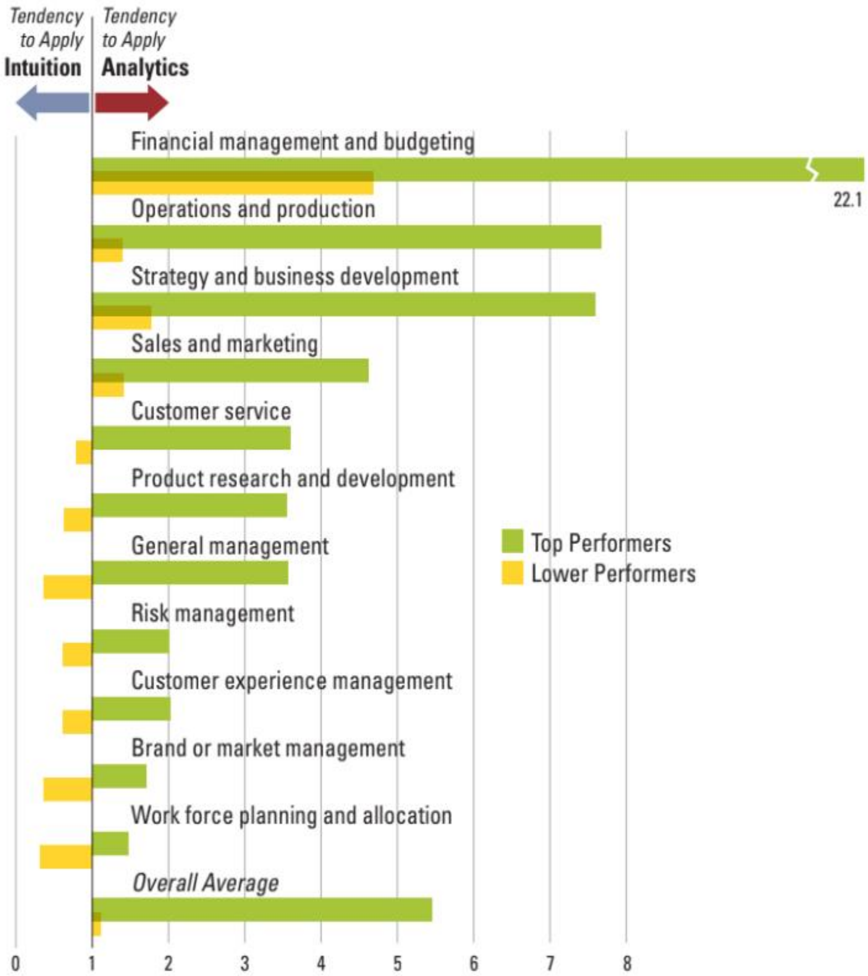

Figure 5: Usage of data analytics in high vs low performers (Hopkins, LaValle et al. 2011)

Big data brings its own set of unique problems related to the three (or four) V's mentioned earlier. Behind those problems lies many valuable opportunities, that will bring value to businesses. When it comes to R&D, big data can affect it in three main ways: inform what innovations companies pursue and how to pursue them, enable more effective innovation processes, and disrupt the corporate playing field by enabling the creation of new business models with big data. (Blackburn, Alexander et al. 2017.)

Regarding informing, big data can help with opportunity assessment, project selection, and even with identifying potential improvement for products. For example, Eastman Chemical Company utilized big data to analyze the 3D printing market with North Carolina State University. It collected consumer responses from social media about Eastman's products and its competitors. The analysis showed that the environmental impact of the product is the main concern. Eastman was able to identify a lucrative market space through big data analytics. (Blackburn, Alexander et al. 2017.)

Big data's effect as an enabler can be seen through helping researchers gain needed information and iterate faster on versions. Big data used with software can help to automatize processes like experimental designs, which can save considerable amounts of resources. Big data tools can also help to manage the information used to support innovation. For example, consulting firm Decernis maintains a large database. They use this large database to help companies create products that comply with different regulations. (Blackburn, Alexander et al. 2017.)

Big data has also the ability to disrupt whole sectors or industries. Big data can drive down costs relating to R&D, which reduces the scale advantages held by large companies and makes the creation of new innovations more available for smaller organizations. Big data is being used to drive better innovations faster and cheaper to the market. Big data is also changing how organizations pursue open innovations, which reduces R&D spending but forces organizations to better manage the flow of ideas and knowledge. In addition, big data makes more efficient analytic processes possible, which can accelerate R&D projects across multiple industries. For instance, the pharmaceutical industry is seeing a great impact from big data in terms of R&D. These changes cause the possibility of disruption to increase substantially which can shape whole industries. (Blackburn, Alexander et al. 2017.)

3 Innovation portfolio management

All investments have potential gains and risks i.e., potential losses. The problem is the word "potential" – we really have no certain way of knowing if the potential will be realized. We can manage this uncertainty by treating the different investments as a portfolio. In a portfolio, the individual investments might hold varying amounts of upside and downside but when combined, the outcome becomes more predictable. Innovations that a company pursues can be thought of as investments where one can try to estimate the gain/risk ratio. Therefore, it is helpful to apply portfolio thinking to innovations inside a company. IPM is “similar to how an investor would treat one's stock portfolio” (Cooper, Edgett et al. 2001).

3.1 How innovation portfolios work

Innovation portfolio management focuses on managing early-stage innovations of a company. IPM helps to guide the development of a concept from the initial idea to the front end of the project portfolio. The innovation portfolio has a clear distinction from a project portfolio, which focuses on the management of products during the development phase. (Mathews 2010.)

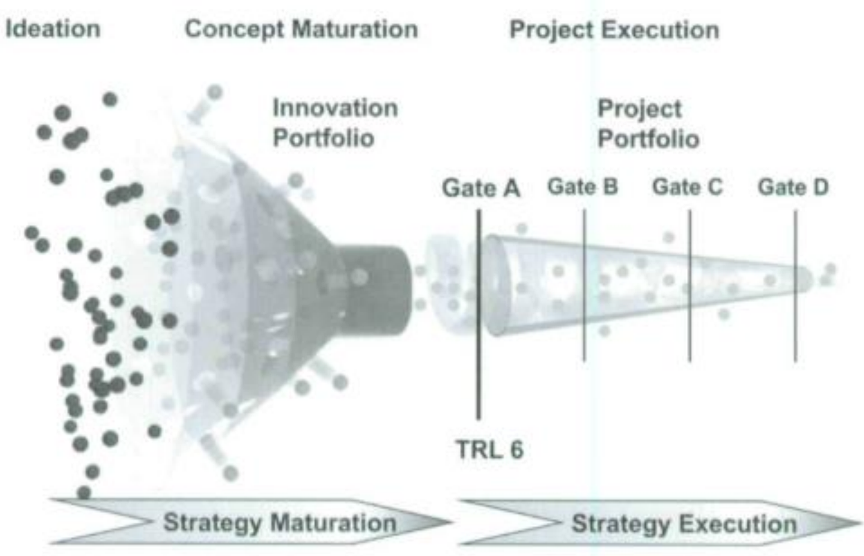

Figure 6: How innovation portfolio connects ideas to development (Mathews 2010)

As can be seen from the figure 6 above, the innovation portfolio works like a funnel for ideas where it collects the ideas, maturates them, and finally delivers the ideas to the project portfolio for further development. The project portfolio has different phases, also called gates which represent a transition from one phase to another. This method is called state-gate, and during every gate, a go/kill decision is made to prune away the weakest projects and allocate resources only to those projects which show more potential (Cooper, Robert G., Sommer

2020a). Gate A can be thought of as the link between the innovation portfolio and the product portfolio. Fig. 6 shows that during this transition TRL is 6. TRL stands for technology readiness level, which is a scale from 1 to 9, where 6 means that the technology has been demonstrated in a relevant environment (European Commission 2020).

The transition phase between the innovation portfolio and the project portfolio is often referred to as the fuzzy front-end. The fuzzy front-end is indeed “fuzzy” and it is hard to pinpoint its exact place in the IPM and PPM process. According to Koen, Ajamian et al. (2001), the fuzzy front-end is all the activities that take place prior to the product portfolio where actual developments are made. This phase stands between ideation and the start of serious investments into development. The fuzzy front-end has been recognized as a vital part of the innovation process and it is where a major part of the information needed should be obtained (Cooper, Sommer 2020).

It is important to understand the differences between the innovation portfolio and the product portfolio because they serve very different functions in the innovation process. However, it is equally important to understand their coherency and how the two portfolios interplay with each other. As previously stated, the innovation portfolio gathers and filters ideas that it feeds to the product portfolio where serious resources are allocated in order to develop and capitalize on these ideas. The direct link between these two – what will be referred as the fuzzy front-end in this thesis – is an important phase where the decision to actually pursue innovation is made.

3.2 Different phases of innovation portfolio

The innovation portfolio is a phased process where the volume of concepts is gradually fined down while the amount of effort and resources per concept is increasing. An innovation portfolio starts with ideation, where ideas are fed into the portfolio. This isn’t yet a phase of the portfolio because the ideation process has very different requirements and it needs a completely different hierarchy. For example, ideation events are a great source of ideas for companies. The threshold for entry to the portfolio should be very low. This will prevent rejecting potentially successful ideas, which are known as *type 2 errors*. For example, FFDT (fast and frugal decision tree) could provide an efficient way of sorting out ideas and concepts. FFDT is a tool that utilizes simple heuristics to quickly approve ideas. (Mathews 2010.)

Concepts enter the innovation portfolio at phase 0. During this phase, a coarse screening is done to define a minimum threshold for concepts to go through to the next phase. The coarse screening is done through qualitative metrics. This can be done with a set of questions that are scored and possibly weighted. The questions should focus on the likelihood of success, and the value and fit for the company. For example, the IRI anchor scales (Davis, Fusfeld et al. 2001) could be a viable option for the initial screening questions. Strategic alignment isn't yet a relevant question because sufficient information is usually gained later to assess strategic aspects of a concept. (Mathews 2010.)

Table 2: Phases of IPM after Mathews (2010)

Phase	Information type	No. of concepts	Days of effort/concept
Ideation	Description	100+	Fraction
Phase 0	Qualitative	80	Fraction
Phase 1	ROM	40	1 or less
Phase 2	Scenario ranges	20	1-2
Phase30	Cash flows & risk management	10	2-3
Gate A ready	Business case & developement plans	5	2

As can be seen from the table 2 above, phases 1 through 3 are for maturing the concepts. Each phase with increasing levels of information, effort, and resources. Every phase is trying to gather enough information to justify pursuing the concept to the next phase. Usually, the number of concepts is halved with every phase. Phase 1 tries to understand the business value proposition of the concept. A ROM (rough order of magnitude) estimation is made, where different attributes are given a value representing the most likely scenario. The attributes are potential revenue, the launch cost, and the margin between these two. When ROM estimates are made, analysts can compare the different clusters of concepts in a graphical representation which is demonstrated in fig. 7. ENVP refers to the expected net present value. Then the portfolio manager can select the clusters that show the most promise and/or are most in line with the company's capabilities. This process allows reducing the number of concepts going forward to phase 2. (Mathews 2010.)

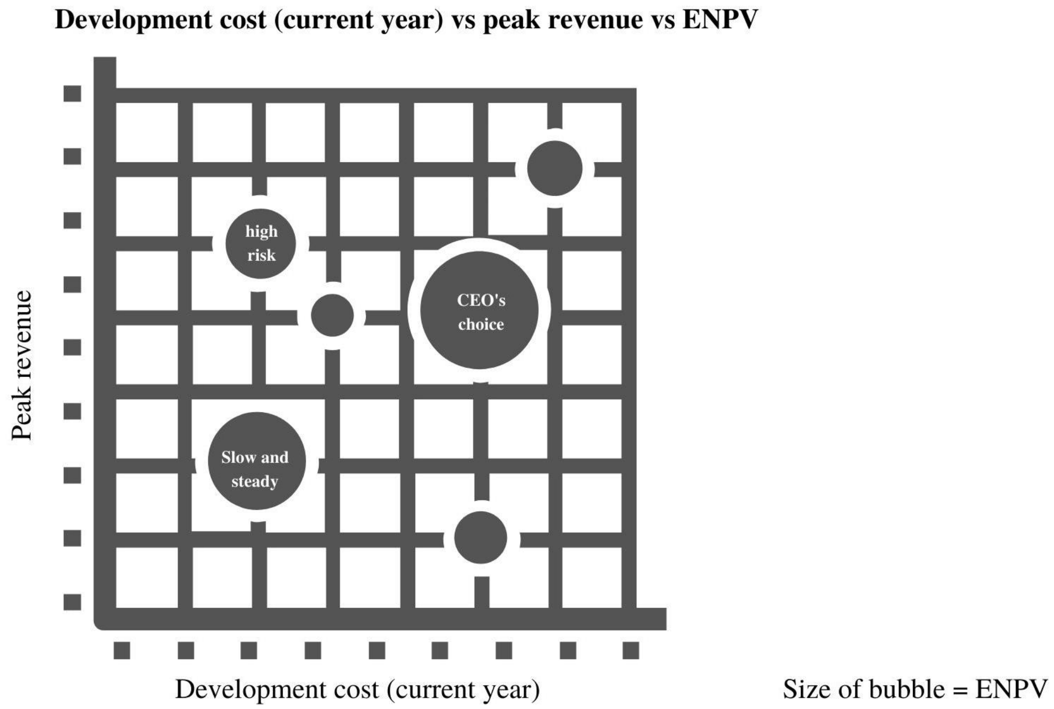

Figure 7: Bubble chart for clusters of concepts after Mathews (2010)

Phase 2 tries to better understand the opportunities and risks of a concept. The initial ROM estimate is fined down, and analysts create optimistic and pessimistic scenarios to create a range for the ROM estimate. Just like in phase 1, these clusters are analyzed against each other to reduce the total amount of concepts going forward to phase 3. (Mathews 2010.)

During phase 3 focus is guided toward the business case: analysis of cash flow and risk mitigation for initial development are made. During this phase, enough information should be gathered to form a clear business case and have the confidence to promote the concept to gate A, which is the beginning of the product portfolio. (Mathews 2010.)

Koen, Ajamian et al. (2001) suggest a different view of the innovation portfolio. Where Mathews splits the innovation portfolio into chronological steps, Koen views the process as a cycle where different phases of the process might happen in various orders. This model represents the activities that happen before the product portfolio and is called the new concept development model (NCD). The model is represented below in figure 8.

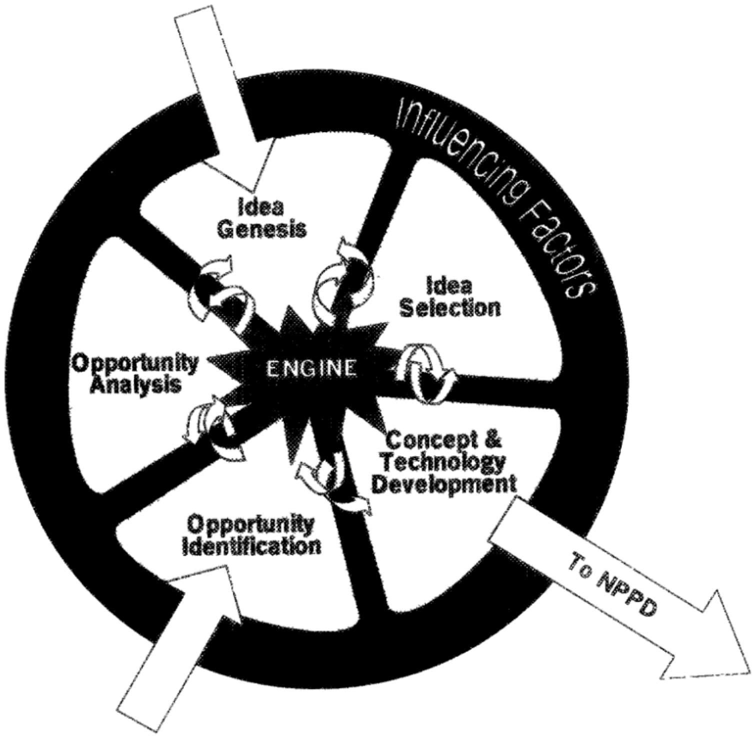

Figure 8: NCD (Koen, Ajamian et al. 2001)

The model is made up of three main parts. The inner circle consists of 5 parts and Koen et. al. (2001) call them “the front-end of innovation”. This term replaces the fuzzy front-end because it aims to bring clearness and controllability to the process. According to Koen et. al. (2001) the term fuzzy front-end suggests that the process is mysterious and uncontrollable which might result in a lack of accountability. The center of the model or the “engine” drives the front-end elements and is fueled by leadership or the culture of an organization. The arrows pointing to the circle represent organizational capabilities, business strategy, the outside world, and enabling science that will be utilized. The circular shape represents the lack of clear order between the five parts, contrary to the model that Mathews (2010) uses.

These two models of the innovation portfolio aren’t the only ones provided in scientific literature, but they give a good cross-section of the innovation process from different viewpoints. During this thesis, the focus is guided towards the phased model that Mathews provides, because the distinct steps allow us to better research the integration of trend recognition to different parts of the innovation process.

3.3 How innovation portfolio management affects business

During the modern business era, IPM has become one of the most important senior management functions. The modern business era has introduced new challenges for companies, like increased global competition, ever faster-changing technologies and innovations, and shorter product life cycles. (Cooper, Edgett et al. 2001.) Because of these challenges, it is increasingly important for businesses to carefully allocate their finite resources.

But why is IPM so critical? This question can be answered by reverse engineering the situation: what harm would a bad IPM process cause? Cooper, Edgett et al. (2001) interviewed company managers and found out that the ramifications of ineffective IPM could be split into 4 levels. First, a lack of strategic consistency will lead to R&D spending that does not reflect the strategic priorities and does not push the company toward its strategic goals. Second, poor IPM will lead to an ineffective go/kill process which means that more projects that don't show high monetary potential will go further into the portfolio pipeline. This causes the company to spend money and time unnecessarily on projects that have marginal value. Third, a lack of focus which leads to a strong reluctance to kill projects because there are no clear criteria for it. This will lead to an arduously long list of projects which means that the resources are spread thin. In this case, the success rate of a project decreases substantially. Finally, poor IPM will lead to poor project selection. Because of the lack of clear selection criteria, decisions aren't based on facts which gives intuition and irrational emotions more space to affect decisions. Often the emotion-based decisions are worse.

The same interview that Cooper, Edgett et al. (2001) conducted asked senior management to list the most critical benefits of IPM and listed 8 key reasons:

1. IPM maximized R&D productivity, which maximizes returns thus maximizing the financial benefit.

2. IPM helps to maintain the competitive position of the business.

3. IPM allows the efficient allocation of finite resources.

4. IPM acts as an interface between project selection and business strategy – the portfolio is the expression of strategy.

5. IPM helps to achieve focus by limiting the number of projects pursued.

6. IPM helps to achieve a balance between projects to optimize the risk-to-reward ratio.
7. IPM enables better communication of values within an organization.
8. IPM provides objectivity to project selection.

Innovation portfolio management allows businesses to succeed in their R&D processes which will lead to an increase in profitability through more efficient monetization of ideas. It will also help companies to maintain their competitive position and grow with the market or in some cases even gain competitive advantages through successful innovation projects.

3.4 Modern challenges of innovation portfolio management

Effective IPM is not easy and there are many challenges to overcome. Many of the challenges have been around for long, but there are also some that have surfaced alongside new business models, faster-changing technology, and big data.

Traditional problems that portfolio managers struggle with still remain. Common IPM challenges include but are not limited to balancing scarce resources, prioritizing projects and choosing the right ones, making go/kill decisions with too little information, and having too many low-value projects going on (Cooper, Robert G., Edgett et al. 2000). These problems are very much linked to each other. They are all caused because the projects need more resources than is available and there is not enough information to make clear decisions on which of the projects are best. The decision to kill a project isn't light – the concept of opportunity cost is very much present in these decisions (Mathews 2010). What if the killed project would have had more monetary value than the ones that were pursued?

The fuzzy front-end, in particular, faces a lot of problems relating to the lack of information mentioned earlier. This phase, which can be thought of as the link between the innovation portfolio and project portfolio, requires lots of information. Arguably, this phase where the decision to start investing and developing an idea is made is one of the most critical ones (Alam 2006). If organizations get this phase right, only the most valuable ideas will go further down the pipeline to development. In order to consistently make the right decisions in the fuzzy front-end, a satisfactory amount of information is needed. Before big data, there was little that could be done to solve this issue. Now data can be used to support or even dictate decision-making. This begs the question of what data should be used and how. Many of the typical problems related to big data arise as the modern challenges of innovation portfolio management.

4 Integrating trend recognition with IPM

Using data as the cornerstone for IPM decisions seems to be valuable. However, it isn't as easy as stating to a company to integrate trend recognition into their innovation process. IPM is a multi-phased system with lots of moving parts. Therefore, it is important to recognize these phases and parts and evaluate where trend recognition might have the greatest impact.

Innovation management has been using VOC to help with decisions regarding innovation before, but the data has been gathered through straight contact with the customers through surveys, interviews, and focus group studies (Melander 2020), which means collecting primary data. In contrast to this, the collected social media data in trend recognition will most likely be secondary or tertiary. Social media platforms and third-party applications enable automatized collection and even analysis of data. This makes the trend analysis much more cost-efficient through secondary or tertiary data and it enables a more scalable analysis. The prejudice of data isn't such a big problem, because in this case the data is collected (and possibly analyzed) by software and not by humans. Also, the more traditional way of using primary data by surveys, etc. might have biases because organizations can guide and manipulate the consumer through the questions they have chosen. Depending on how deeply companies wish to dive into the trend analysis, secondary or tertiary data should be used. Naturally, secondary data allows more in-depth analysis whereas tertiary data offers a lighter solution by producing pre-made analysis.

In this section, the thesis will research how and where trend recognition could be integrated into IPM. The integration might happen during a certain phase, method, or evaluation. Depending on where trend recognition is used, it will order different values to the process either as a facilitator of ideas or as a contributor to estimates.

4.1 Trend recognition in different types of IPM

Strategy affects the innovation process. The strategy formation process is typically split into two parts: formulation refers to the process of planning and setting goals while implementation refers to putting the strategy into practice (Mintzberg 1978). However, to succeed in these parts the formulator must be fully informed, and the environment must be stable meaning that the information cannot change after the strategy has been formulated (Mintzberg 1990). Naturally, this is not the case in the actual business environment. From this, two different strategies that can be used in IPM emerge: emergent and deliberate (Mintzberg, Waters 1985). These two types vary especially regarding the agility of the process. Emergent IPM is not planned and is a lot more dynamic, whereas deliberate IPM is planned, stiffer, and a more classical way of conducting portfolio management (Mintzberg, Waters 1985). Underneath in fig. 9 the differences between deliberate end emergent strategies are visualized.

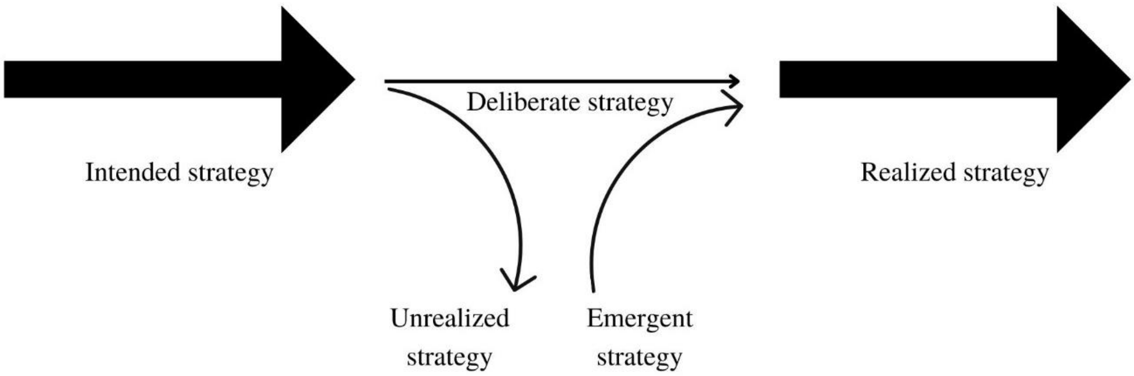

Figure 9: The formation of different strategies after Mintzberg (1978)

In the deliberate version, enterprises utilize the predefined corporate strategy, which is used to conduct a project-level strategy. This strategy is then used to align the company's innovation portfolio. (Kopmann, Kock et al. 2017.) The clear downside of this method is the lack of agility. We live in an ever-changing business environment where it is hard to conduct an accurate long-term market forecast. The increasing turbulence and tough competitive environment make adaptability and thus agility very important for an organization's survival

(Kopmann, Kock et al. 2017). Emergent IPM strategy acknowledges the high volatility of the business environment. It allows companies to sense and adapt to changes. (Kopmann, Kock et al. 2017.) According to the research conducted by Kopmann, Kock et al. (2017), emergent strategy recognition correlates positively with product portfolio success. This suggests that the dynamic structure of the portfolio could benefit the process. If agility helps the product portfolio, it might have similar effects to the innovation portfolio which is a more dynamic process by nature (Cooper, Robert G., Edgett et al. 1999).

Within the frameworks of these two methods, data utilization would be a more logical fit for the emergent strategy. It seems that ideas produced by emergent methods might be of lesser quality and the ideation phase lacks sufficient tools (Heising 2012, Kock, Heising et al. 2015, Kopmann, Kock et al. 2017, Mathews 2010) – challenges that trend recognition and analytics can bring relief to. Also, the reactive nature of trend recognition requires sufficient dynamic capabilities from an organization, which further strengthens the notion that trend analysis fits better in the emergent strategy.

The lesser quality of the ideas might be the cause of information overload (Sparrow 1999). When ideas are being created by sensing the outside world, the volume of ideas created rises too high causing their quality to decrease. Also, it is hard to tell what ideas are worth pursuing and which aren't. Data analytics and trend recognition could help to solve these problems and produce higher-quality ideas. Trend recognition brings a clear framework from which ideas can be derived which limits the volume of ideas and makes the ideation process much more distinct. It also helps to increase the quality of ideas, because the ideas derived from trend recognition already have some baked-in potential.

Trend recognition could be also used in the deliberate strategy to get support for the strategic decisions. Even though the ideas have to fit inside the framework of the conducted strategy, trend recognition could bring assurance to this phase. The fit for trend recognition isn't as pronounced as it is in the emergent approach but recognizing some longer-term trends would bring some poise to forming the strategy.

The emergent and deliberate approaches could be thought of as a spectrum of agility in the IPM process rather than a binary choice. Organizations don't necessarily have to conduct strategy carved in stone and limit their innovation portfolio to it. Organizations don't also have to manage their portfolio without any high-level strategy. In fact, the research of

(Mintzberg 1990) could be interpreted as that a fully deliberate strategy is somewhat of an illusion and that all strategies have characteristics of an emergent strategy because the environment has unseen variables. Companies that fail to realize this have not cultivated their dynamic capabilities to a sufficient level. Implementing deliberate strategy and recognizing emerging strategy are complementary in their effect on project portfolio success (Kopmann, Kock et al. 2017). Therefore, a hybrid between emergent and deliberate approaches might have the most benefits. For example, a company could form a high-level strategy that guides the focus toward some objective and limits the scope of ideation. Then it could analyze the changing climate and look for trends, which it could dynamically utilize in the ideation phase or later during portfolio management. This would be a rough example of a hybrid model between emergent and deliberate approaches utilizing trend analysis.

4.2 Trend recognition in different phases of IPM

Trend recognition has potential applications in various phases of IPM. In this section, the thesis will be referencing the phases stated in chapter 3.2. Integration, in this case, doesn't necessarily mean that the whole analytic process should be done during the part where the "integration" happens, but that the information gained from the analysis will be used in that part. The integration could also happen at different levels:

- Ideation-level, which technically isn't yet a phase of IPM (Mathews 2010), where trend recognition could be used as a facilitator.
- Phase-level where trend recognition could be used as the gatekeeper for proceeding from one phase to another.
- Method-level where trend recognition could be used as a tool in an evaluation.

To further understand how trend recognition could be integrated into IPM, the thesis will go through the possible use cases within each phase.

4.2.1 Trend recognition in the ideation phase

The thesis will first look at the ideation-level integration. Because ideation isn't a structural phase of the innovation portfolio (Mathews 2010), ideas can be produced quite freely with different methods, like with the ideation events mentioned in chapter 3.2. The ideation phase has two main challenges: how to create ideas and how to filter the ideas. Trend recognition could offer help with both of the issues.

When it comes to the filtering of ideas, trend recognition offers a clear filter: the idea should have some relevant consumer trend behind it. However, the threshold to enter the innovation portfolio should be as low as possible (Mathews 2010) which means that using trend recognition as a stand-alone gatekeeper could be harmful because it rises the threshold for entry. Organizations could utilize the FFDT mentioned in chapter 3.2 and questions about consumer trend alignment could be integrated into the FFDT.

Trend recognition has arguably bigger potential regarding idea creation. The data for trend recognition is gathered from social media, which constantly produces huge volumes of data. This opens the possibility for constant ideation. Social media data could be analyzed constantly to produce insights about consumer trends that are relevant to the organization. This process of ideation by constant analysis would produce higher volumes of ideas and concepts. These concepts would already have some tangible reasoning: the underlying consumer trends. According to Mathews (2010), the ideation process should produce a high number of ideas and concepts without using too many resources. As was discussed earlier, IPM has traditionally gathered information about the VOC through primary data, which requires more resources. This limits the usage of VOC during ideation and can also result in smaller sample sizes that may fail to represent the full target audience. Trend recognition through SMA doesn’t have this problem so it has much bigger potential as a tool for the ideation phase. With trend recognition through SMA, organizations can utilize VOC in the ideation phase efficiently. Trend recognition would work as a facilitator where social media data would constantly pour into the analysis process where consumer trends could be recognized and strengthened over time with a high level of automation. To back this conclusion up, Kohli and Jaworski (1990) suggest that companies should systematically employ trend recognition and repeatedly check that concepts align with trends. This process would facilitate high-quality ideas efficiently that could enter into the innovation portfolio.

4.2.2 Trend recognition in phases 0-3

Trend recognition can be also utilized in the actual phases of IPM. Some phases seem to be more suitable than others. Thus, different phases will be getting uneven amounts of attention in this chapter.

Phase 0 carries out a rough qualitative assessment. Because the portfolio has a high number of concepts during this phase, the assessment per concept should not take too much effort. This creates a problem – trend recognition analysis requires effort. The results of the trend analysis could be useful in this phase, but it would make phase 0 much stiffer thus causing more harm than good. If an organization wishes to use trend recognition as a core part of phase 0, it could be integrated into the set of screening questions. The question could challenge the concept by asking if it's aligned with the recognized and prioritized trends. (McGrath, MacMillan 2000) suggest a set of statements that help with establishing a ROM estimate. The statements are provided in table 3. Trend analysis can provide needed information to better evaluate some of these statements, for example, regarding long-term demand and demand growth.

Table 3: Assessing demand for ROM (McGrath, MacMillan 2000)

A. Positive indicators of favorable demand structure.
- The potential long-run market demand for the solution we offer is enormous.
- The demand will grow for a long time.
- There are many critical problems we can solve by pursuing this business.
- There are many potential sub-markets we might be able to tap by pursuing this business.
- The beneficiaries of the final product/services are willing and able to pay, or can be easily funded.
- The demand will not be satisfied with only one purchase by the beneficiary—purchase will be repeated.
- The repeated usage will be frequent.
- There are many potential products and services we can offer by investing in this business.

B: Negative indicators.
- The customer's perception of value will be dependent on the backing of other parties.
- The sale of the product will depend on contribution of effort and resources of other parties, like distributors.
- The market demographics are likely to change substantially against us.
- The offering serves an emotionally sensitive market (e.g., risks to babies).
- We may be exposed to long-term legal liabilities if we pursue this business.

During phase 1 a ROM is conducted, where revenues and launching costs are estimated. Trend recognition could be used when estimating the monetary value of concepts. Let's use a fictitious company – a streaming service that offers movies and series to consumers, which has been a fruitful industry in the 20th century (Statista 2022c) – as an example to understand how trends could be used to help with revenue estimations. The company has recognized consumer trends related to the streaming industry using the SMA methods introduces in previous chapters, one being the trend of cloud gaming, which according to Statista (2022c) will grow from 1,48 billion U.S. dollars in 2021 to 6,3 billion in 2024, an increase of 426%.

Cloud gaming means that consumers pay a monthly fee, which gets them access to a wide selection of games on a platform. The company has estimated that the concept might be worth 30 million USD in revenue per year. By realizing that the concept has a strong tailwind from the underlying trend – cloud gaming – they can improve their estimates. The company predicts itself to have a one percent market share and estimates that the market size for cloud gaming will be 6,3 billion as mentioned earlier. This means that the potential revenue would be closer to 60 million per year than 30 million. Naturally, the consumer trend isn't the only metric for estimating potential revenue, but it can bring some needed information to have a more accurate estimate. As a real-life example, Netflix - a big player in video streaming – has clearly recognized the trend of cloud gaming and has brought games to their offering. They are also acquiring a Finnish mobile game developer Next Games for 65 million euros (Netflix 2022) which will help with the creation of new mobile games. Netflix is a good example of how high-quality organizations utilize trends in their innovation management and R&D.

This process of making valuations regarding R&D with the aid of market and trend analysis is covered in the academic literature and discussed in the "real options" concept which allows for more accurate valuing of projects with uncertain outcomes (Newton, Paxson et al. 2004). According to (Lint, Pennings 1998), the first part of options analysis in R&D is to examine the maximum budget of the R&D from an economic view. This can be done by evaluating the size of the relevant market, its growth rate, the expected market share, and market profitability (Lint, Pennings 1998). The previously mentioned example of the fictitious streaming company utilizes this approach of using market intelligence to estimate a suitable valuation.

Phase 2 develops the ROM further with scenario ranges. Trend recognition could be utilized especially when estimating what the monetary potential would be in a positive scenario. Concepts that have the tailwind of a trend naturally have increased monetary potential. When a company has recognized relevant trends, it is easier to say if concepts align with the trends and thus estimate an upper limit for revenues. The potential utilization of trend analysis in phase 2 is most likely similar to phase 1. The positive scenario is the one where consumer trends bear fruit, and the negative scenario is where the trends do not materialize to the fullest. Similar to phase 1, trend analysis in phase 2 can learn from the aspects of real options reasoning.

Trend analysis can also help with phase 3, where more accurate cash flow estimates are calculated for every scenario made in phase 2. Cash flow estimation is a function of money in, and money out, so naturally trend analysis can't single-handedly provide accurate estimates. The value of trend analysis is that it provides additional information to the analysis.

Trend recognition doesn't necessarily have to be integrated into a specific phase of the innovation portfolio. The innovation portfolio is a nonlinear process during which concepts are matured and evaluated (Mathews 2011), which means that concepts are evaluated multiple times during their journey through the portfolio. Therefore, trend recognition can be used as a tool during the whole journey of the concepts. If the analysis part for trend recognition is done separately from the actual phases of the innovation portfolio, the gained information could be used to frequently check if concepts align with wanted trends. This could be useful because both the concepts and trends could change during the maturation of the concepts. Andreassen, Lervik-Olsen et al. (2015) suggest that companies that systematically check the trend alignment of concepts become more market-oriented, can develop new services that match with consumers' future needs, and can better communicate the benefits of innovation during launch which will improve commercialization.

4.3 Challenges of using trend recognition in innovation portfolio management

Trend recognition can be somewhat short term and it might not help with creating a long-term strategy. Therefore, the focus should be guided toward bigger-picture trends. This has some problems: how to know what are long and what short-term trends? Also, how one can recognize long-term trends that aren't already known by the industry and thus don't help in gaining a competitive advantage?

The usage of trend recognition in IPM can be split into different phases, which all possess different challenges. First, there is the SMA part, where the collection and preparation of large volumes of data rise issues. Second, there is the act of recognizing trends which has its own unique set of challenges. Third, the information has to be used efficiently in IPM, which creates new challenges.

SMA problems are quite similar to the problems related to big data, as discussed in chapter 2.3. The biggest challenges are that the mere volume of social media data is so big and that the data is very unstructured. Also, the velocity – the speed that new data is being produced

– is a common problem of social media data. This makes it hard to store the data and find valuable insights from it. Because of these challenges, it is impossible to manually control and analyze the data, which arises a need for tools such as AI and machine learning to automate the analysis. (Stieglitz, Mirbabaie et al. 2018.) This reinforces the previous recommendation in chapter 4.2.1 of using a high level of automatization when integrating trend recognition into IPM. In IPM, the problem of high velocity isn't as present, because data analytics doesn't have to happen hourly, minute-to-minute, or second-to-second. IPM deals with limited resources and has to make decision processes effective, as discussed previously in the thesis, so it is not realistic to make decisions so often. However, continuous analysis can still bring value, because the insights are supported or challenged by increasing amounts of data.

During this thesis, trend recognition has been viewed as a method of SMA. Trend recognition has its own problems that are beyond the usual SMA challenges, but data analytics actually finds solutions to some of these challenges. Andreassen, Lervik-Olsen et al. (2015) recognized some problems in trend spotting: methods most frequently used by practitioners, like interviews, focus groups, and surveys focus on current markets, and there is a lack of qualitative trend spotting. The lack of qualitative analysis is partially due to the anecdotal approach and the reliance on environmental observations (Andreassen, Lervik-Olsen et al. 2015). Consequently, SMA has the ability to bring relief to these challenges. Deciding which trends hold the most value or stand the test of time is another challenge of trend analysis. Obviously, not all trends are equally promising so it is the organization's responsibility to decide which trends they will pursue. Also, it is challenging to recognize trends that aren't already widely known or regarded as important. Things like sustainability, digitalization, or urbanization are important trends, but they are widely known thus they don't bring significant competitive advantages. The key is to notice the consumer trends before competitors do to gain a first mover advantage (Lieberman, Montgomery 1988). This is a trend recognition problem but also an analytics problem. Solutions could be found through the usage of different data analysis methods provide earlier in the thesis.

The challenges that slow organizations from becoming data-driven are often related to competency, culture, and strategic integration (Hopkins, LaValle et al. 2011). It is important to use the information on consumer trends effectively in IPM. The innovation portfolio has many phases, so managers need to decide where the information is best used. In other words, the question of where analytic insights should be used becomes an important operational challenge (Hopkins, LaValle et al. 2011). Chosen trends should align at least loosely with the strategic intent – a vegan cosmetics brand probably shouldn’t pursue a meat-related trend. This raises the question of high strictly should the pursued trends reflect the company’s strategy to have some focus but also avoid type 2 errors. Also, how much emphasis should the recognized trends have in the valuation of concepts? In addition to these problems regarding how organizations should utilize trend knowledge, there is also the problem of agility. Organizations have to have sufficient dynamic abilities to react to the information gained from the trend analysis. This might arise some challenges regarding the corporate structure. If organizations aren’t able to react to the stimuli from their environment, what is the purpose of analyzing the environment?

5 Value proposition for innovation portfolio management

High-performing companies utilize data analytics much more than low-performing companies (Hopkins, LaValle et al. 2011). It seems quite clear that data-driven business management is generally valuable for organizations. Also in 2021, 75 percent of organizations ranked innovation as a top 3 priority (Boston Consulting Group 2021). If data-driven management is very valuable and innovation management is one of the most important management roles, utilizing data analytics in innovation management could bring quite significant value to organizations. According to Blackburn, Alexander et al. (2017) big data can bring significant value to the R&D process.

In 2005, between 70 to 90 percent of US fast-moving consumer goods products were withdrawn from the market one year after launch (Gourville 2006). The poor performance is not only evidence of inadequate anticipation of consumers’ future needs, but also a call for innovators to spot emerging trends that will impact consumers’ lives. Successful trend recognition will improve the odds of innovating something of value to consumers. It will also aid innovators in detecting new opportunities by facilitating the usage of idea-generation tools. (Andreassen, Lervik-Olsen et al. 2015).

Trend recognition helps solve traditional problems of IPM regarding the fuzzy front-end. Improving data integrity in the fuzzy front-end where ideas and investments connect is a major challenge. During the front-end, most of the information should be obtained. Studies show that the reasons for new product failures are largely due to bad front-end work. (Cooper, Robert G., Sommer 2020b.) Trend recognition through data analysis might help alleviate this problem by offering consumer sentiment information from a new source thus bringing substantial value to IPM. The fuzzy front-end could be way less fuzzy if customers are involved in the front-end stages of NSD (new service development) (Alam 2006). This statement could be expanded to IPM generally. When integrating trend recognition into IPM, organizations involve the customer in the process. This is not done through direct contact with the customer (primary data) which has been done traditionally, but by listening to the customer through social media data which is secondary or tertiary data. This is much more cost-efficient and scalable. Trend analysis through SMA can also help alleviate some biases associated with traditional surveys or interviews. If organizations use both the traditional way and trend recognition in parallel and triangulate between the results, they could control the biases both ways which might result in the best outcome.

Another value of trend recognition for IPM is that when done right, organizations can gain a first mover advantage. If organizations recognize trends early enough – before competitors - they can gain market share by being the first or one of the first in the market. The order of market entry and market share correlates positively and evidence for superior market share for first movers is strong (Jakobsen 2007, VanderWerf, Mahon 1997). However, there isn’t a correlation between the order of entry and performance because the order of entry is more likely a tradeoff between market share and increased risks/costs, even though competent organizations could leverage the high market share to increase performance (Jakobsen 2007). If an organization doesn’t wish to pursue a first mover position because of the increased risks, it can adopt an early follower strategy (Jakobsen 2007). This might be beneficial because the risks are decreased but the organization can still enjoy a higher market share from being one of the first movers. Trend recognition enables the utilization of both of these strategies.

As stated at the beginning of the thesis, the research is not about trend forecasting. Obviously, accurate forecasting of trends would bring significant value to organizations. However, the bottleneck wouldn’t be how trend forecasting could be used in IPM, but how trends could be forecasted in the first place because the sheer act of predicting the future is extremely hard. Studies in strategic management have developed two opposing principles around this topic: they should either try harder to accurately predict future trends or be so agile that they are able to adapt fast to emerging trends (Vecchiato 2015). On the surface, it would seem like this thesis would focus on the former, but actually, the approach fits better with the latter school of thought. The research of the thesis focuses on how organizations could integrate trend recognition into IPM to react fast to the changes in consumer trends. This approach emphasizes agility and is reactive, rather than proactive.

Recognizing trends early enough allows organizations to move before their competitors. This is possible due to the diffusion of innovation. The diffusion of innovation refers to the life cycle that innovation goes through. It describes the different phases and how the popularity of the innovation changes from one phase to another. The diffusion of innovation is closely correlated with the product life cycle. Both have a development curve that resembles an upside-down U-letter. Also, both of them have five phases. Because the diffusion of innovation has different phases, it is enough that we recognize trends early enough – we don't have to forecast them fully. The phases that innovations go through are *innovators*, *early adaptors*, *early majority*, *late majority*, and *laggards* (Meade, Islam 2006). The diffusion is shown in fig.10 below where the cumulative adoption and new adaptors are showcased separately. As can be seen, if an organization is able to recognize and react to consumer trends during the "innovators" -phase of the life cycle, it has the possibility to capitalize on a given consumer trend. If this process is done effectively and consistently, it could provide a clear competitive advantage to an organization by making the organization a pioneer or a very effective early follower. The act of recognizing trends can also mitigate some of the usual risks that come with being a pioneer because the innovations that are pursued are backed by an uprising trend.

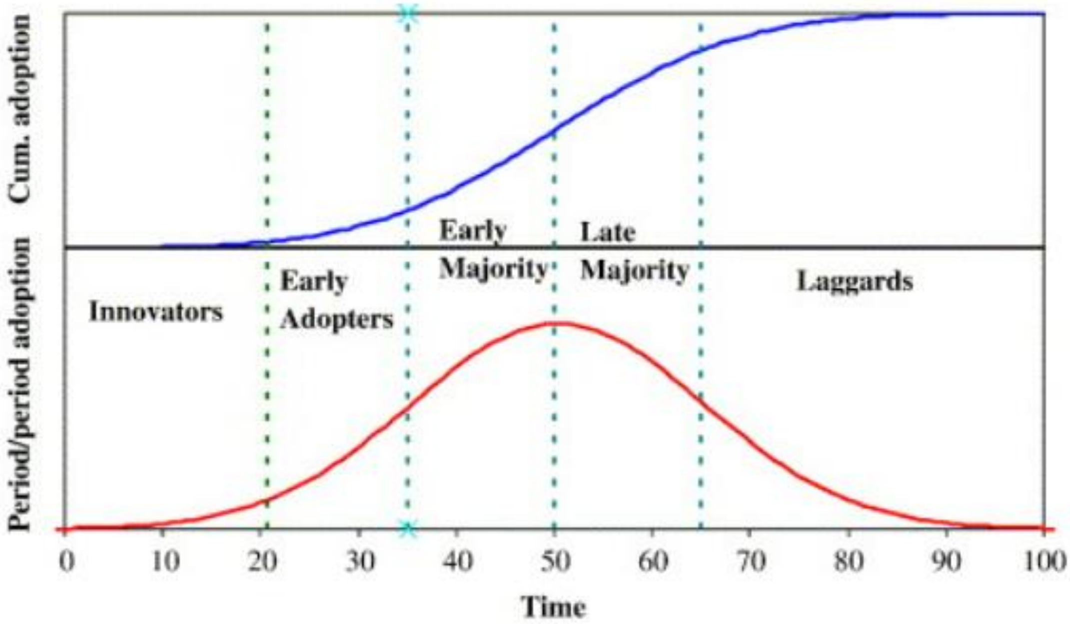

Figure 10: The diffusion of innovation (Meade, Islam 2006)

Trend analysis offers organizations a way to collect consumer information from a new viewpoint and from a new data source compared to traditional ways. It seems to bring value by helping to produce higher-quality concepts efficiently and ideally before competitors. Also, it can be valuable as a supporting source of information during different estimates in the innovation portfolio.

5.1 A step-by-step framework for integration

In response to the aforementioned challenges and opportunities, the thesis has proposed a framework for integrating the trend analysis process into the innovation portfolio. The goal of this integration framework is to provide innovation managers with a more concrete step-by-step framework that lets organizations utilize the information provided by the trend analysis effectively. The framework aims to provide instructions on how the integration could be done in order to create value for IPM – not on the exact methods that should be used to achieve value.

The framework includes the following steps:

1. **An evaluation of the business and consumer environment**. This allows organizations to identify interesting ideas to guide focus toward. It is not recommended to start with strategic alignment, because the threshold for accepted trends should be as low as possible, just like during the ideation phase where the threshold is set low to avoid type 2 errors. The scanning of the environment enables organizations to see the bigger picture and familiarize themselves with the characteristics of their own field. This step also helps organizations to understand who are included in their customer base which prepares organizations for the next step. If an organization frequently evaluates their environment, this step can be skipped.

2. **Thorough research of the customer base**. During this step organizations should really get to know their target audience. Because the trend analysis is done through social media data, it is important to understand how the target audience behaves. Through this research, organizations should be able to answer who are their customers and target audience, which social platforms they use, and how they use them. The question "how" is particularly hard and requires lots of research because this includes things like who they follow, how often they use social media, and how they interact there (images, video, audio, text, etc.). As was discussed earlier in chapter 2.3, social media analytics can be done through many different methods and the type of data is an important factor.

3. **Recognize trends through social media analytics**. The quality of the information provided in this step dictates how successful the process is. How trends should be recognized depends fully on the organization, its services or products, and the customer base. However, it is likely to be beneficial to use multiple methods to analyze the social media data because different methods have different strengths and weaknesses. The key is to find trends that are in the early stages of the diffusion of innovation in order to gain a competitive advantage through the gained knowledge. These upcoming trends aren't as likely known by the competitors. It wouldn't be wise to use the organization's resources to analyze trends that are already widely known.

4. **Create, sustain, and refine a database of trends**. A database for information on consumer trends is very valuable. It allows companies to go back to the information, challenge it, learn from it, and through continuous analysis refine it. Especially the continuous analysis and refining of the information has the potential to create

considerable competitive advantages. This makes the information increasingly accurate and comprehensive, which can cumulate with time. If an organization analyses consumer trends for years and refines an existing database of consumer trend information, it can gain a profound grasp on consumer trends and their development in their field.

5. **Use this database with different phases of IPM**. The gained knowledge can now be leveraged to make more accurate assumptions about concepts. As can be seen from the framework, the actual analysis isn't integrated into a certain phase of the innovation portfolio, but rather make the analysis its own phase which creates valuable information that flows into IPM. This allows organizations to use consumer trend information during any – or every – phase of the innovation portfolio. The ways that the information can be used in different portfolio phases were discussed during the earlier chapters of the thesis.

Even though the framework is presented as step-by-step instruction, it isn't a linear flow from one step to another. The process should be thought of more as a continuum where different steps are done at varying intervals. Parts 1 and 2, which are more general business and marketing intelligence actions, should be updated in fewer intervals, for example, once a year. This is because they aren't as prone to rapid changes and their function in the process is background work to help the actual trend analysis. Parts 3 and 4 are the actual analysis and refining of the information, which should be treated as a continuum. These functions should be highly automatized to sustain continuous analysis cost-effectively (Stieglitz, Dang-Xuan et al. 2014). Also, social media data is very high in volume and velocity (Stieglitz, Mirbabaie et al. 2018), which makes the manual analysis extremely challenging.

6 Conclusions

The thesis was inspired by the realization that the modern business world may have bypassed the IPM methods provided in the academic literature. I wanted to research how modern tools could be integrated into IPM and decided to focus on consumer trend recognition as the analytic tool for modernizing IPM.

The research question of the thesis was "how innovation portfolio management could be improved with trend recognition?". The thesis provided multiple possibilities for the integration of trend analysis into IPM and provided a framework that innovation managers can use to effectively use trend analysis in IPM. According to the research of the thesis, customer trend recognition brings value to IPM by providing solutions to existing problems and by offering alternative tools for market intelligence. The traditional ways of collecting VOC have utilized primary data and have been based on direct contact with the consumer. This has many downsides, such as resource heaviness and biases that affect the quality of the data. Trend recognition through SMA offers a new cost-efficient and scalable way for organizations to hear the VOC with the utilization of secondary and tertiary data and a high degree of automation. It can also help to remove the biases that the primary data had because it allows consumers to release data without corporate interference, which can increase the quality of data. However, this means that the collected data will be more unstructured, which causes challenges on the analysis front.

The information gained from trend analysis helps to create better quality ideas and monitor existing concepts during their maturation in the innovation portfolio. This helps to bring more promising ideas to the product portfolio which can in turn lead to a higher likelihood of commercial success. However, to fully benefit from the results, organizations have to have sufficient dynamic capabilities to react to the insight gained from the trend analysis. The research of the thesis also found that continuous trend analysis could provide a compounding competitive advantage over time because organizations would get increasingly in tune with their customer base. This knowledge would naturally help to generate better concepts. Also, trend recognition in IPM opens up possibilities for organizations to pursue either first mover or early follower strategies.

6.1 Managerial implications

The innovation portfolio is an essential part of an organization and providing attractive innovations to the market is crucial for the organization's longevity. Not only the innovation managers but also other senior management should stress the importance of producing high-value innovations consistently and effectively. The result of the thesis affirms that management should utilize data analytics in their innovation processes and that trend analysis has its own role in strengthening the innovation process. The analytics process shouldn't be tied to a specific phase of the innovation portfolio because the results could be utilized in many places in the process. The analytics process should emphasize the role of continuous analysis to gather increasingly accurate insights on consumer trends. These insights could be used to facilitate more high-quality ideas or in different estimates during the maturation of concepts. By using the framework provided in the thesis, managers can integrate the analytic process into IPM effectively. This framework could potentially be used similarly with other fields of analytics or with other business processes, although further research should be done on the benefits of these actions on a case-by-case basis. To reap the benefits of trend analysis in IPM, managers have to ensure that their organization has the ability to analyze the social media data, manage the increasing database of consumer information and that the organization is agile enough to quickly enforce the insights gained from the trend analysis.

6.2 Limitations and possibilities for future research

The thesis implicitly assumes that IPM is an important field of business which makes the challenge of improving it meaningful to organizations. Also, the thesis assumed that consumer trends can be recognized and that it can be done through the data created by consumers on social media. Thus, the thesis focused on the value that data analytics and trend recognition bring to business and on the IPM challenges that they might solve. The research was limited to consumer trends from social media data and to the innovation portfolio and didn't include, for example, the product portfolio. Also, the research focused on trend recognition rather than forecasting.

This thesis opens up many research areas regarding trend recognition and the R&D process. First, research on other platforms than social media as a data source for consumer trend analysis is needed. Social media data has problems, as the loud minorities can create interferences in the data. These issues could be avoided through some other platforms. Also, could insight from different platforms be used together to create a more accurate analysis? Second, further research on how organizations should shape their innovation process to be more agile is needed. In trend recognition, the ability to quickly react to the environment is important because that is the only way that organizations can take advantage of the diffusion of innovation. Thus, agility becomes important if organizations wish to use trend recognition in their R&D. Finally, the notion that trend recognition is the better way of being ahead of the competition can be challenged by researching the effects of actual consumer trend forecasting on IPM. This would require research on if organizations can consistently forecast consumer trends and if forecasting would bring added commercial value. There's the possibility that, for example, acting on the predictions would be a tradeoff between risk and return or that the timing would bring challenges for commercialization thus making the process not worth the effort.

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