FAKULTÄT FÜR INFORMATIK
Faculty of Informatics

Recommender Systems in the Domain of Early-stage Enterprise Investment

Investment Decision-making & Venture Valuation

DIPLOMA THESIS

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Diplom-Ingenieur

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Business Informatics

by

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Vienna, 27th April, 2018

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I hereby declare that I have written this thesis independently, that I have completely specified the utilized sources and resources and that I have definitely marked all parts of the work - including tables, maps and figures - which belong to other works or to the internet, literally or extracted, by referencing the source as borrowed.

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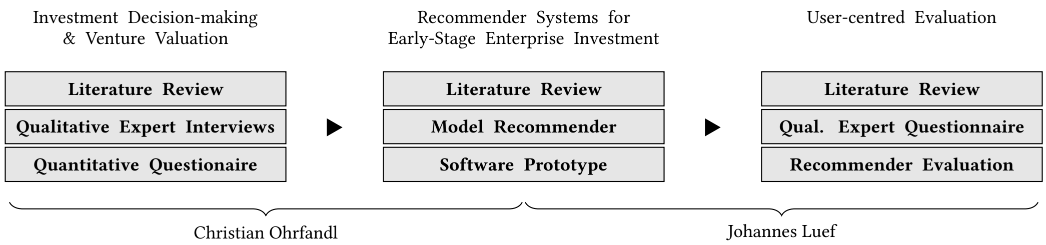
Vienna, 27th April, 2018

Johannes Luef

Distinction of Joint Work

The present research is conducted as joint work between Christian Ohrfandl and Johannes Luef. Each author elaborates a specialization topic including individual research questions. Additionally, chapter 3 *Recommender Systems for Early-Stage Enterprise Investment* is jointly constructed by both authors. The results are composed as two separate theses, each assigned a different subtitle.



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First of all, I want to thank Prof. Hannes Werthner for providing me with the opportunity of conducting this thesis. Additionally, I want to thank Dimitris Sacharidis, MSc, PhD for all of our discussions about the thesis and the domain of recommender systems in general. Furthermore, I want to thank Johannes Luef —co-author of the present work—for the excellent cooperation in developing the shared chapter and for his *duties* as beloved friend. Subsequently, I want to thank all of my friends for not forgetting about me, even though I was not able to return my loyalty as much as I should have had.

Finally—and most importantly—a special thank goes out to my partner Elisabeth and my family, for it is you who were the light, guiding me through this very journey and lighting my way in times of darkness.

I want to conclude by quoting a famous poem by Friedrich Nietzsche, best describing my *diploma voyage*:

> “Krumm kommen alle guten Dinge ihrem Ziele nahe. Gleich Katzen machen sie Buckel, sie schnurren innewendig vor ihrem nahen Glücke – alle guten Dinge lachen.
>
> Der Schritt verrät, ob einer schon auf seiner Bahn schreitet: so seht mich gehn! Wer aber seinem Ziele nahe kommt, der tanzt.
>
> Und, wahrlich, zum Standbild ward ich nicht, noch stehe ich nicht da, starr, stumpf, steinern, eine Säule; ich liebe geschwindes Laufen.
>
> Und wenn es auf Erden auch Moor und dicke Trübsal gibt: wer leichte Füße hat, läuft über Schlamm noch hinweg und tanzt wie auf gefegtem Eise.
>
> Erhebt eure Herzen, meine Brüder, hoch! höher! Und vergeßt mir auch die Beine nicht! Erhebt auch eure Beine, ihr guten Tänzer, und besser noch: ihr steht auch auf dem Kopf!
>
> *Nietzsche [2013]*
> *(orig. Also sprach Zarathustra: Ein Buch für Alle und Keinen, 1883 – 1885)*”

Abstract

The main objective of this thesis consists of the design of a recommender system, representing a novel method concerning the computational recommendation of early-stage enterprises to investors. In order to quantify decision rules the recommender system is based on, investors' requirements and behaviours need to be analysed utilizing qualitative- and quantitative research. Furthermore, demonstrating the behaviour of the proposed recommendation algorithms is a major task of this thesis. For this reason, a prototype of the recommender system is being crafted in software. Due to the fact that the usability of the recommendation system's user interface plays a key role in terms of recommendation quality, a usability- and recommendation quality review of the prototype is being conducted in the course of empirical research.

Based on the results of the *Investment Decision-making & Venture Valuation* specialization topic, it can be concluded that the most important characteristics investors base their investment decisions on, are stated as the quality, size and composition of the management team, product- & public interest and the industry / market sector of an early-stage enterprise. Furthermore, the venture valuation methods most utilized by investors, most meaningful in terms of valuation quality in the context of early-stage enterprises and most beneficial when utilized in a recommendation system, are stated as the scorecard- and berkus methods. Finally, investors' requirements among the functionality of a recommender system in the domain of early-stage enterprise investment may be concluded as the construction of an investor profile.

The shared chapter 3 *Recommender Systems for Early-Stage Enterprise Investment* addresses the conceptualization of a recommendation system in the domain of early-stage enterprise investment based on the findings of co-author Christian Ohrfandl's specialization topic *Investment Decision-making & Venture Valuation.* The resulting recommender system includes various types of recommenders in a parallelized approach, that is, Collaborative filtering, content-based-, knowledge-based-, social- and hybrid recommendation algorithms. Additionally, the conceptual model of this recommender system has been implemented as a highly scalable, plugin-based software prototype that may be easily extended by different recommendation algorithms in future work.

The most important opportunity for future research is stated as qualitative- or quantitative evaluations of recommendation quality in terms of user satisfaction. These evaluations may answer the question, whether the implemented design decisions improve a user's utility when using the system. In fact, it is precisely this very evaluation that is being researched by co-author Johannes Luef in the course of the specialization topic *User-centred Evaluation.*

Contents

CHAPTER 1

Introduction

The global financial crisis of October 2008 highly influenced the European economic market. According to the *Organisation for Economic Co-operation and Development (OECD)* and *Eurostat*, especially *new firm registrations* declined and *bankruptcies* increased in countries having a high level of financial development (such as Germany, France or non-OECD member economy USA) [Klapper and Love, 2011; OECD, 2016; Eurostat, 2016a]. In the last few years, economies of the EU-28 member states slightly recovered from the crisis and therefore, EU-wide enterprise entries rose by 6.8% in 2013 compared to 2012[1] [OECD, 2012; Eurostat, 2016b]. Especially the birthrate of enterprises in Austria rose by a mean of 8.1% during 2013 – 2015, indicating a total of 294.648 company births since the beginning of the financial crisis [WKO, 2016]. Klapper and Love [2011] argue that a positive and continuous birthrate of enterprises is the key factor for thriving innovation and is essential for the proceeding of the economic market's dynamics. Consequently, financing of new companies must be guaranteed in order to increase the birthrate of enterprises. Predominantly, funding of ventures is addressed by investors such as *Business Angels* or *Venture Capital Funds*, who provide capital particularly needed in the early stages of the company formation and beyond. However, as a result of the considerably large amount of enterprises entering the European market, potential investors face the problem of *information overload*. Due to its nature, information overload in the domain of venture valuation leads to the inapplicability of traditional *investment decision-making* criteria needed for managing an investor's investment portfolio. Therefore, the need for information filtering techniques based on computational *recommendation systems* emerges.

The main objective of this thesis consists of the design of a recommender system, representing a novel method concerning the computational recommendation of early-stage enterprises to investors. In order to quantify decision rules the recommender system is based on, investors' requirements and behaviours need to be analysed utilizing qualitative- and quantitative research. Furthermore, demonstrating the behaviour of the proposed recommendation algorithm is a

[1] 2012: excluding Greece; 2013: excluding Greece, Ireland and Poland

major task of this thesis. For this reason, a prototype of the recommender system is being crafted in software. According to Jannach et al. [2010, pp. 186, 187], the usability of the recommendation system's user interface plays a key role in terms of recommendation quality. Thus, a usability- and recommendation quality review of the prototype is being conducted in the course of empirical research. Finally, the following research questions will be answered:

(i) How can investment decision-making requirements and behaviours of investors be quantified for being used in a recommender system? [Christian Ohrfandl]

  (a) Which investment decision-making criteria are crucial to investors?

  (b) Which data needs to be provided by early-stage enterprises in order to be of interest to investors?

(ii) Which venture valuation methods best model the characteristics of early-stage enterprises? [Christian Ohrfandl]

(iii) How do the identified investment decision-making characteristics and venture valuation methods affect the model of a recommender system in the domain of early-stage enterprises? [Christian Ohrfandl]

(iv) Which recommendation algorithms and -techniques shall be considered in a computational recommendation system in the domain of early-stage enterprise investment, in order to guarantee highly personalized recommendations for investors? [Christian Ohrfandl, Johannes Luef]

(v) How can the *cold start problem* in the context of computational recommendation systems in the domain of early-stage enterprise investment, be addressed? [Christian Ohrfandl, Johannes Luef]

(vi) Which constraints does a software prototype of the computational recommendation system need to fulfil, in order to guarantee technical- and algorithmic feasibility? [Christian Ohrfandl, Johannes Luef]

(vii) How does the recommendation quality and the usefulness of the recommendation system affect user satisfaction? [Johannes Luef]

  (a) How may the recommender system be evaluated in terms of recommendation quality and how do the findings affect future research?

  (b) Which methodologies may be utilized to evaluate the recommendation system and which implications do the results indicate?

1.1 Expected Results

The main outcome of this thesis is stated as the construction of a usability improved prototype of a computational system capable of delivering highly personalized recommendations of early-stage enterprises to investors. In the course of this thesis, qualitative- and quantitative research is conducted in order to analyse investors' venture valuation criteria. Whereas the results of qualitative research (such as expert interviews or literature review) help identifying investors' investment decision-making criteria, the findings obtained by quantitative research (such as a questionnaire) quantify the gathered data and therefore highly affect the final design of the underlying recommendation system. Finally, modelling of the prototype's user interface design is needed to support the investor in exploring and filtering the entrepreneurial market. Thus, the recommendation quality of the algorithms will be evaluated in the course of qualitative research (such as expert interviews or offline evaluation testing respectively).

1.2 Methodology

The methodological approach consists of the following steps:

(i) Literature review and research on investors' investment decision-making criteria and -behaviours. To the authors' best knowledge, very few publications are available that discuss the issue of recommendations in the domain of venture valuation.

(ii) Research is conducted in a qualitative- and quantitative manner in order to gather significant data needed for modelling the recommender system.

(iii) Based on the data provided by the previous task, the purpose of this subtask is to specify recommendation algorithms that generate highly personalized recommendations of early-stage enterprises fitting investors' needs.

(iv) After successful specification and design of the recommendation system, a prototype is crafted in software.

(v) Finally, recommendation quality of the algorithms is reviewed in the course of empirical research.

1.3 State of the art

Due to its interdisciplinary nature, the *state of the art* of this thesis is considerably broad. Therefore, the remainder of this section is divided into three parts, each addressing research on the corresponding field of science, that is, *Venture Valuation*, *Recommender Systems* and *Usability Engineering*.

Venture Valuation is one of the key concepts of this thesis, as it provides necessary calculation models needed as input of investors' decision-making criteria. Although research on the valuation of ventures has become very popular in the last decade, little attention has been given to the field of innovative early-stage enterprises. One major characteristic of early-stage enterprises is the absence of profit combined with a rapid growth in revenue especially in the early stages of the venture [Rudolf and Witt, 2002, p. 259]. Unlike the traditional valuation models such as the *intrinsic value method*, this behaviour needs to be addressed by valuation models not solely relying on profit. Rudolf and Witt [2002, pp. 67, 81] argue that the *earnings value-* and *Discounted Cash Flow (DCF)* approaches extended by life cycle phases and phase models respectively, fit the initial characteristics of early-stage enterprises. Finally, a previous study conducted by A.-K. Achleitner et al. [2004] indicates that 25% (50% respectively) of the interviewed investors utilize the earnings value- and DCF approaches for the valuation of ventures in the growth phase.

Recommender Systems have become an independent research area during the mid-1990s with roots in the fields of cognitive science, approximation theory, information retrieval, forecasting theory, management science and marketing [G. Adomavicius and Tuzhilin, 2005]. Nowadays, conferences and special interest groups such as *ACM Recommender Systems (RecSys)*, *ACM Special Interest Group on Information Retrieval (SIGIR)*, *User Modeling, Adaptation and Personalization (UMAP)* and *ACM Special Interest Group on Management Of Data (SIGMOD)* actively contribute to the field of recommender systems [Ricci et al., 2010]. However, to the authors' best knowledge, very few publications are available in the literature that discuss the issue of recommendations in the domain of venture valuation. Recently, Stone, Zhang, and Zhao [2013] and Zhao, Zhang, and Wang [2015] have proposed a new approach on addressing the problem of risk-hedged venture capital recommendation from a risk management perspective. The researchers proposed five algorithms analysing investors' investment behaviour and showed that the newly predicted investment opportunities compared to the *CrunchBase*[2] dataset lead to significant performance improvements in the context of recommendation quality. Nevertheless, a key limitation of this research may be seen in the fact that investors' human characteristics such as the level of risk aversion and personal interests on investment categories have not been taken into account. Hence, as indicated in the previously, focussed research on investors' needs is the most important part of this thesis and, consequently, a prerequisite to the specification of the recommender system.

Usability Engineering as a discipline of human computer interaction plays a vital role in the user interface design of the recommendation system's prototype. In recent years, innovative approaches to human interaction design have emerged in the form of *usability guidelines* supporting developers in the design of interfaces [Shneiderman and Plaisant, 2016, p. 75]. Companies dominating the IT market such as Microsoft[3] or Apple[4] provide their own usability guidelines on how to interact with their systems. The main objective of these guidelines is stated as the standardization of task sequences that allow users to perform tasks in the same sequence and manner across similar conditions. Previous research has demonstrated that the consequent use of standardized task sequences reduces the user's workload [Shneiderman and Plaisant, 2016, p. 75]. However, information dashboard design has become popular in recent years as being a uniquely powerful tool for communicating important information. As reported by Few [2006, p. 97], the fundamental challenge of dashboard design involves information

[2]Crunchbase is an internet platform offering the discovery of innovative companies and their staff: https://www.crunchbase.com/

[3]Usability guidelines Microsoft: https://developer.microsoft.com/en-us/windows/design

[4]Usability guidelines Apple: https://developer.apple.com/ios/human-interface-guidelines/

filtering and representational techniques. Nevertheless, other sophisticated approaches can be found in the literature. Shneiderman and Plaisant [2016, pp. 152-155] analyse and compare various aspects of expert reviews. The results obtained by Shneiderman and Plaisant suggest that expert reviews may occur early or late in the design phase. Furthermore, the authors claim that expert reviews are an effective way to improve the design quality of the user interface. Additionally, the authors' attention was not only focused on expert reviews but also on usability testing. The emergence of usability testing is an indicator of the profound shift in attention towards users' needs [Shneiderman and Plaisant, 2016, p. 156]. Finally, in order to guarantee a high quality interaction design, the aforementioned research concerning usability guidelines and dashboard design highly contributes to the outcome of this thesis.

1.4 Relevance to the Curriculum of Business Informatics

The study of business informatics focuses on the link between humans, organizations and information technology. In addition, *information processing* plays an important role in organizations and society. In the last few years there has been a growing interest in the subject of research-driven teaching of information- and communication systems in economics and society [TU Wien, 2013]. As a consequence, research on the analysis, modelling, design, implementation and evaluation of such systems has become very popular. In particular, the curriculum of the business informatics study highly correlates with the interdisciplinary characteristics of this thesis:

(i) *Innovation (188.915)*
The focus of the course Innovation lies on the evaluation of innovative projects utilizing case studies and business models. The implementation of a prototypical system based on business ideas is an assignment of the course.

(ii) *Business Intelligence (188.429)*
The course Business Intelligence plays a vital role in fundamental data mining technologies and their applications such as big data analysis. The educational objective of the course lies in the selection and application of appropriate data mining algorithms on a given dataset. The learning content is used to gain experience in different data mining techniques.

(iii) *Econometrics for Business Informatics (105.628)*
The focus of the course *Econometrics for Business Informatics* lies on the calculation of elementary econometric models and methods. In particular, the outcome of the recommendation algorithm will employ econometric models in order to improve decision-making processes.

(iv) *Beyond the Desktop (183.639)*
The course *Beyond the Desktop* focuses on the understanding, interpretation and adaptation of human computer interaction methodologies. The graphical user interface of the prototype needs to support investors' needs.

(v) *Advanced Software Engineering (180.456)*
A solid understanding of software development and architectural design is an important requirement for the creation of the recommendation system's prototype.

CHAPTER 2

Investment Decision-making & Venture Valuation

2.1 Background

The very purpose of the current section lies in the elaboration of basic concepts of the *venture valuation*- and *investment* research domains. Furthermore, a terminology of *entrepreneurship*, *finance* and *economics* that is applied throughout the present work, is being established and introduced to the reader.

2.1.1 Terminology

The following passages introduce the reader to the terminology utilized in the course of this specialization topic.

Enterprise

An enterprise—also referred to as *company*, *business* or *venture*—is an economic entity serving as the main site of the entrepreneur's business operations, who, in turn, constitutes a *natural* or *legal* entity. The aim of an enterprise is commonly defined as the increase of the *enterprise value* [Macharzina and Wolf, 2008, p. 15; Meyer and Bloech, 2006, p. 26]. More formally, the purpose of an enterprise is the transformation of certain input factors into higher-valued output factors in the course of value-creating processes [Macharzina and Wolf, 2008, p. 15]. In contrast to private households whose domestic requirements are distinguished by the consumption preferences and needs of its residents, the characteristic feature of an enterprise is the *external requirements coverage*, that is, an enterprise supplies goods or services in order to meet the demand of other (*external*) business entities [Kühler, Küpper, and Pfingsten, 2007, p. 132]. In order to turn an enterprise's input- into output factors, corresponding domain knowledge and the appropriate amount of (human) resources are needed. Although prima facie the output of an enterprise may solely be seen as the produced goods or services, there are factors that *implicitly* profit from the applied value-creating processes. It is the *symbiosis* of labour creation, eduction of employees, participation in cultural- or sporting activities et cetera that results in adverse effects on society [Macharzina and Wolf, 2008, p. 15]. However, the most important incentive of an enterprise founder lies in the *freedom of choice*.

Being treated as the core aspect of economic independence, freedom of setting its own objective lies upon the fundamental principles of entrepreneurship. Naturally, the economic objective of an enterprise shall yield the institution- and orientation of action and may therefore be addressed as the *spirit of optimism* in an economic perspective. Yet it is the enterprise that is challenged by precisely this economic independence that formerly presented itself as the very essence of the entrepreneurial spirit worth aspiring for. It is daily fare that enterprises continuously need to act upon the dynamics of their *internal-* and *near economic environment* (for instance stakeholders such as personnel, customers, suppliers or competitors), thus, constituting an enterprise's *dynamic character*. In order to cope with this situation, *individual initiative* and *-planning*, *economic decision-making* and, subsequently, taking *responsibility* for the enterprise and all its stakeholders, are commonly regarded the requirements to becoming a successful entrepreneur. As a consequence, it may be concluded that the *luxury* of economic freedom as part of entrepreneurship combined with the dynamics of the economic market, comes at a high price: *economic risk*. [Macharzina and Wolf, 2008, p. 16]

According to Macharzina and Wolf [2008, p. 16], *economic* risk on the one hand arises from economic independence, yet economic independence arises from the willingness to take economic risk. Therefore, this type of risk is generally defined as endangerment of business continuity and classified into *composite risk* (such as integrity of intellectual property), *external risk* (for instance availability of financing) and *internal risk* (for example the identification of market trends) [Henderson, 2001, pp. 23–24]. Categorized into equity risk, exchange rate risk, interest-rate risk et cetera, it is *market risk*—an entity of the internal risk domain—that yields a considerably large amount of dynamics to an enterprise's market position. Market risk is delimited from other forms of financial risk such as operational- or credit risk and commonly originates from anomalous shifts in market prices or -rates arising from a volatile economic environment. There exist various forms of environment volatility originating from different sources such as the stock- or commodity market and exchange- or interest rate [Dowd, 2007, pp. 1, 3]. A different aspect of economic risk constitutes from the types of risk originating from an enterprise's individual maturity level. Thus, enterprises are commonly categorized by their *life cycle-* or *investment stages*.

Enterprise Life Cycle

The enterprise life cycle spans from the very moment of innovating a business idea to the foundation of an enterprise until the so called *exit*—the disposal—of the enterprise. The cycle is mainly determined by three financing stages, that is, the *early-*, *expansion-* and *late stage* [A. Achleitner and E. Nathusius, 2004, pp. 9–10]. The first stage of the enterprise life cycle from a chronological perspective is the early stage that, in turn, is categorized into the *seed-* and *start-up* stages. During the seed stage, entrepreneurs are commonly engaged with the definition of the product idea and market analysis, while in the start-up stage the priority lies on the foundation of the enterprise and the development of product maturity. Member enterprises of the early stage commonly face the problem of finding themselves in the red. This circumstance arises from the fact that expenses such as research and development (R&D) or the cost of living exceed revenue. For this reason, the early stage is also referred to as the *valley of death*[1]. In order to reach the zone of profit and therefore, the approach of the expansion stage, entrepreneurs are reliant upon funding, which is predominantly based on the owner's equity capital, public grants and venture capital (the reader is referred to subsection 2.1.1 for a more elaborate analysis). After successful structuring of the enterprise and reaching the loss / profit break-even point, the enterprise enters the expansion stage.

The expansion stage—the successor to the early stage—heralds the start of production and the entry to the economic market. Marking the survival of the valley of death, enterprises of the expansion stage commonly transition from the loss- to the profit zone. In particular, the major aim of the expansion stage may be seen as the —in some cases even nearly exponential—rise in profit. However, with great expansion comes the need for additional and higher funding rates in order to elevate production levels and secure the market position. Thus, entrepreneurs can not solely rely on public grants or venture capital anymore, but rather consider targeting external financing and private equity as funding source. When the market position and rise in revenue starts decreasing, the transition to the late stage is imminent. [A. Achleitner and E. Nathusius, 2004, p. 10]

Finally, the late stage marks the last of the three financing stages and basically addresses the *initial public offering (IPO)* or exit of the enterprise. The characteristic element of the late stage lies in the deflation of the revenue curve, signalling saturation of the market. For that reason, entrepreneurs usually intend to expand to other—yet unknown—markets. This task may be accomplished by different strategies, which are therefore distinguished by the type of the late stage, that is, *bridge* or *management-buy-out (MBO)*[2] / *management-buy-in (MBI)*[3] [A. Achleitner and E. Nathusius, 2004, pp. 9–10]. The bridge type of the late stage is chronologically located before the MBO/MBI and basically addresses the preparation of either a disposal of the enterprise or IPO. As mentioned at the expansion stage, funding sources such as external financing and private equity also apply to the bridge type. If the aim of the bridge stage was the IPO, the main focus of funding is accomplished by issuing stocks at the stock market. Once problems such as the rise in competition or restructuring of the organization are overcome and the revenue curve finally tends to reach its peak, the enterprise is taken over in the course of an MBO or MBI.

For a visual representation of the venture life cycle stages, the reader is referred to Figure 2.1. The present work mainly focusses on the seed- and start-up stages and therefore, the main research entity is defined as the *early-stage enterprise* type.

[1] The time period between the foundation of the enterprise and the transfer from the loss- to the profit zone is commonly referred to as *valley of death* [Maughan, 2010].

[2] MBO: Enterprise takeover in the course of acquiring enterprise capital from the owners by the management [Herman, (Warszawa)., and Przedsiebiorstwie., 2009, p. 112].

[3] MBI: Enterprise takeover by external management [Herman, (Warszawa)., and Przedsiebiorstwie., 2009, p. 112]

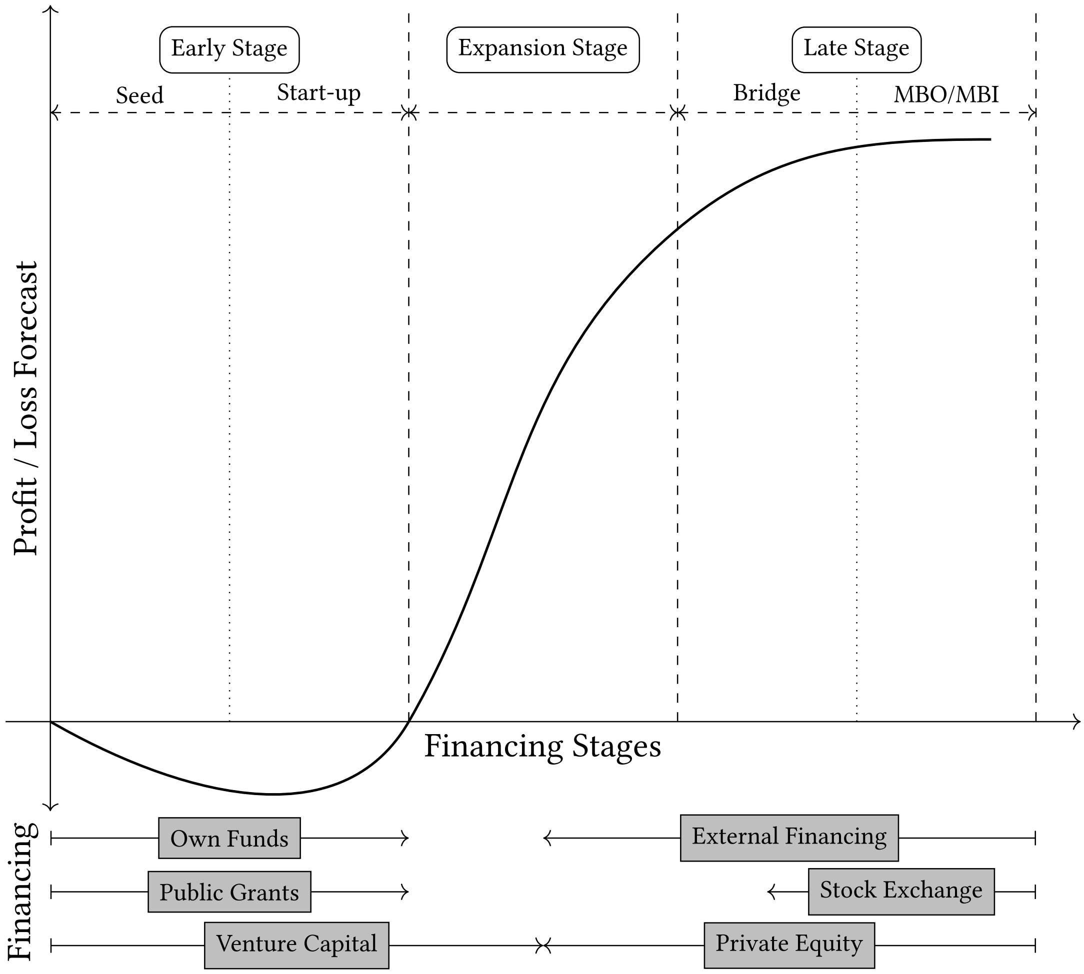

Figure 2.1: Life cycle / investment stages of enterprises.

Source: Based on A. Achleitner and E. Nathusius [2004, p. 10]

Early-stage Enterprise

Early-stage enterprises are members of the seed- and start-up stages of the enterprise life cycle and therefore, they mark the very beginning of entrepreneurial careers. The term *early-stage enterprise* is a very important term that is being utilized throughout the present work and is therefore characterized in detail in the present passage. Early-stage enterprises are generally distinguished regarding their foundation according to the following characteristics: [A. Achleitner and E. Nathusius, 2004, pp. 1–6; K. Nathusius, 2001, pp. 4–6; Wickham, 1997, p. 374]

(i) Degree of founder independence

(ii) Structural existence

(iii) Growth potential

(iv) Degree of innovation

(v) Characteristics specific to early-stage enterprises [A. Achleitner and E. Nathusius, 2004, pp. 4–6]

   (a) Deficiency in a representative history of business activities
   (b) Scarcity of resources
   (c) Importance of intangible assets
   (d) Flexibility requirements
   (e) Upside potential vs. downside risk
   (f) Entrepreneurial vision

The Degree of Founder Independence is defined as the intended status of independence of the founder and is mainly distinguished between a *dependent-* and *independent foundation*. Dependent founders are usually employed by existing enterprises and manage the foundation process of an enterprise in the course of their employment at an existing enterprise. Therefore, the founded enterprise inherits a direct relationship from the originating enterprise. Common cases of application may be seen in the foundation of affiliated companies, joint ventures, business areas or branch offices. Independent founders, in turn, are not bounded to an originating enterprise and therefore, they mainly address problems originating from self-financing and collateralization of credit risk. [K. Nathusius, 2001, pp. 5–6] The present work will not elaborate on dependent- but rather focus on the independent foundation of enterprises.

Structural Existence is differentiated between *derivative-* and *distinct foundations*. The founding of an enterprise is to be considered derivative, if there are existing enterprise structures constituting the parent company. The set of derivative foundations include organizational legal forms such as the holding company or joint ventures and business formation in the course of a merger or spin-off. Distinct foundation, on the other hand, is defined as the formation of existence without the possibility of reverting to an already existent tangible- or intangible entrepreneurial asset (such as franchising as part of the business plan). [K. Nathusius, 2001, p. 4] The present work will not elaborate on derivative foundations but rather focus on the distinct foundation of enterprises.

The Growth Potential of an enterprise plays a key factor considering the potential future success of an enterprise and is commonly determined by the goals of the founder [A. Achleitner and E. Nathusius, 2004, p. 2]. Depending on the growth potential of foundations, three types of enterprises may be distinguished as follows: *Low-*, *moderate-* and *high growth* enterprises [Bygrave and Zacharakis, 2009, p. 359]. As indicated by its name, low growth enterprises exhibit a low growth potential (less than 10m USD in revenue over five years). The major characteristic of low growth enterprises may be seen as the lifestyle motives of the founder and therefore the foundation of an existence rather than the generation of high profit. According to A. Achleitner and E. Nathusius [2004, p. 2], 90% of all enterprise foundations are low growth enterprises.

In contrast, moderate growth enterprises—the second classification category concerning the growth potential of enterprises—map the area between low growth- and high growth enterprises in terms of revenue, that is, 10–50m USD over five years. Bygrave and Zacharakis [2009, p. 359] define the major characteristics of moderate growth enterprises as regional- or focused businesses that basically focus on the recognition of new opportunities. 9% of all enterprise foundations are moderate growth enterprises [A. Achleitner and E. Nathusius, 2004, p. 2].

The final classification category subject to the growth potential of enterprises is preserved for high growth enterprises, indicating revenue of over 50m USD over five years. According to A. Achleitner and E. Nathusius [2004, p. 2], only 1% of all enterprise foundations are classified as high growth enterprises. The main characteristic of high growth enterprises is the strategic alignment towards the generation of profit. Furthermore, high growth enterprises commonly operate in trend-setting industry sectors such as information technology or entertainment. Due to the fact that these markets are considerably young, they exhibit high dynamics and therefore feature the potential of high revenue that, in turn, comes at a high risk. However, indicating high growth enterprises is addressed via the analysis of the valuation subject[4]'s growth compared to the growth of other enterprises listed in the same industry sector. A common metric for measuring growth is the comparison of input factors (such as the amount of employees) against output (such as revenue or profit). [A. Achleitner and E. Nathusius, 2004, pp. 2–3]

For a visual representation of the summarized characteristics of the enterprise types compared to their growth potential, the reader is referred to Table 2.1.

Table 2.1: Enterprise types in subject to their growth potential, based on Bygrave and Zacharakis [2009, p. 359].

	Low Growth	**Moderate Growth**	**High Growth**
Business type	Local / Lifestyle	Regional / focused business	High-potential industry
Organization	Efficient systems, entrepreneur in charge	Delegation, budgets, control systems	Decentralization, elaborate control systems
Leadership	Founder	Founder (team) and management	Professional management

To be continued…

[4]The valuation subject in the context of this paper conforms to the enterprise about to be valuated.

…continued from previous page

	Low Growth	Moderate Growth	High Growth
Strategy	Dynamically act upon changes of the economic environment	Identification of (new) opportunities, renew source of differentiation	Portfolio of investments (highly innovative products, extension of current advantages)
Resources	Money provided by the four Fs (see subsection 2.1.1), local banks and savings	Equity money (investors such as BAs)	Venture capital, BAs, investment banks, exit strategy (IPO, disposal)

The Degree of Innovation of an enterprise is distinguished into *innovative-* and *imitating foundations* depending on the type of the corporate concept [K. Nathusius, 2001, p. 5]. Furthermore, the degree of innovation defines the extent an enterprise is able to yield an innovation [A. Achleitner and E. Nathusius, 2004, p. 3]. The business model of innovative foundations are based on innovations, that is, state-of-the-art products or services of young and highly dynamic markets such as the information technology- or telecommunications industry sectors. The corporate concept of imitating foundations, in turn, is modelled on existing enterprises and therefore, ordinary cases of imitating foundations may be seen as taverns, diners, barbers, fashion- or footwear stores. According to A. Achleitner and E. Nathusius [2004, p. 4] there exists a link between the degree of innovation and an enterprise's growth potential, that is, there exists a high probability that innovative foundations develop high growth potential. As a consequence, highly innovative enterprises may gain monopoly in their corresponding market, which is also referred to as the *first-mover advantage*. However, due to high risk (such as the market acceptance risk), these enterprises commonly face the so called *first-mover disadvantage* as well. [A. Achleitner and E. Nathusius, 2004, p. 3]

Deficiency in a Representative History of Business Activities is the de facto main problem of valuating early-stage enterprises. The reason can be seen in the fact that these enterprises commonly have not conducted any business activities and therefore do not possess a historic track record. [A. Achleitner and E. Nathusius, 2004, p. 4]

Scarcity of Resources may be seen as major problem preventing the generation of rapid growth and arises from the fact that early-stage enterprises commonly miss financial- and subject-specific support. In order to overcome this problem, early-stage enterprises commonly rely on external funding that, in turn, provides the necessary means to invest in crucial domains such as R&D, marketing or sales. As pointed out earlier, early-stage enterprises also need—in addition to financial support—subject specific-support such as knowledge concerning legal issues, accounting and networking with customers or suppliers. [A. Achleitner and E. Nathusius, 2004, pp. 4–5]

The Importance of Intangible Assets especially applies to early-stage enterprises of high-tech industry sectors (such as the automotive-, information technology- and telecommunication industry sectors) and mainly concerns patents, rights, procedural- and system knowledge. Securing intellectual property with patents holds the advantage of building a monopoly on certain knowledge and, on the other hand, may generate profit by selling licences to competitors, allowing the use of the corresponding knowledge. Therefore, knowledge is the de facto key factor yielding competitive advantage. Especially in high-tech industry sectors, intangible assets are considered the major factor of success. [A. Achleitner and E. Nathusius, 2004, p. 5]

Flexibility Requirements —another characteristic especially applicable to early-stage enterprises—address the strength of an enterprise to successfully cope with the dynamics of the economic market and position itself on the market [A. Achleitner and E. Nathusius, 2004, p. 5]. For instance, enterprises need to constantly track competitors and their innovations in order to react to the emerging dynamics of the economic market. Based on the assertions of Schumpeter [2003, pp. 82–83], early-stage enterprises have the ability to quickly act upon the market's needs, innovate and subsequently, *disrupt* long-established business processes. In fact, early-stage enterprises may be seen as the de facto incarnation of Schumpeter's terminology of *creative destruction*—also referred to as *Schumpeter's gale*—that is:

> “ …The fundamental impulse that sets and keeps the capitalist engine in motion comes from the new consumers' goods, the new methods of production or transportation, the new markets, the new forms of industrial organization that capitalist enterprise creates. …
>
> *Schumpeter [2003, pp. 82–83]* ”

and

> “ …The opening up of new markets, foreign or domestic, and the organizational development from the craft shop and factory to such concerns as U.S. Steel illustrate the same process of industrial mutation—if I may use that biological term—that incessantly revolutionizes the economic structure *from within*, incessantly destroying the old one, incessantly creating a new one. This process of Creative Destruction is the essential fact about capitalism. It is what capitalism consists in and what every capitalist concern has got to live in. …
>
> *Schumpeter [2003, p. 83]* ”

Upside Potential vs. Downside Risk of early-stage enterprises marks the major scientific research topic of the present work. Due to the fact that there is literally no knowledge or historic track record available at the time of enterprise foundation, the probability of upside potential and downside risk balance each other. For that reason, A. Achleitner and E. Nathusius [2004, pp. 4–5] classify early-stage enterprises as highly risky assets. Finally, the last major characteristic affecting an enterprise's economic success lies in the motivation and vision of the *entrepreneur.*

Entrepreneurial Vision —the undoubtful believe in the enterprise's output and its implications on the surrounding world—belongs to the core concepts of the economic strategy and defines the normative orientation of the enterprise. Wickham [1997, p. 374] argues that the vision of an entrepreneur positively affects the thrive of an enterprise, if aligned properly. Therefore, the researcher proposes the implementation of a *mission statement* as management tool, effectively enhancing business performance by improving stakeholder communication and business strategy.

As pointed out earlier, one major drawback of the seed- and start-up stages lies in the early-stage enterprise's need for external funding in order to prevent bankruptcy until reaching the expansion stage. Therefore, entrepreneurs rely on external investments.

Funding

Funding enables early-stage enterprises to generate rapid growth and is commonly realised by internal- (such as the *four Fs*) and external funding conducted by stakeholders such as *public funding agencies*, *investors* (for instance *business angels* or *venture capitalists*) and *business incubators* or *-accelerators*. The following passages elucidate internal- and external funding including the corresponding stakeholders in great detail.

The Four Fs —an abbreviation for *founders, family, friends, fools*[5]—mark the very first type of funding from a chronological perspective: internal funding. As the abbreviation reveals, the first timespan of an early-stage enterprise is funded by capital obtained by the four Fs. However, the money invested by the four Fs barely suffices for enterprise foundation. Therefore, additional sources of funding (such as external funding) need to be exploited. [Rudolf and Witt, 2002, p. 26]

Public Funding Agencies are commonly operated by the government, state-affiliated organizations or universities and ordinarily allocate certain grants early-stage enterprises may apply for. The grants themselves may include monetary funding (such as loans) as well as intangible assets (such as education or training in entrepreneurship and economics) that are legally contracted under certain conditions (such as the refund of a loan). A special case of funding agencies can be seen in universities who try to bridge the gap between R&D-driven academic projects and the possible result of enterprise foundations. However, characteristics of public early-stage enterprise- and R&D funding agencies vary depending on the originating country. [Czarnitzki and Fier, 2002, p. 1; AustrianStartups, 2017; aws, 2017; FFG, 2017; netidee, 2017]

[5] The latter (fools) states the fact that funding in the course of the early stage is highly risky due to the enterprise's non-existent historic track records and the founders' non-liability.

Investors such as *business angels (BAs)* and *venture capital firms (VCs)* fund (early-stage) enterprises by the investment of capital. Monetary assets invested by private investors (such as BAs or VCs) are also referred to as *external equity capital* or *private equity* due to the fact that the distribution of capital is not organized via an official capital market (such as the stock market). Private funding is generally based on *informal*- and *formal* equity capital, whereas BAs conduct funding of *informal* equity capital and venture capital—capital funded by VCs—is classified as *formal* equity capital. The reason for this distinction lies in the fact that VCs establish funds that, in turn, are utilized for the investment into enterprises. For this reason, VCs are ordinarily able to invest a considerably higher amount of capital than BAs. [Rudolf and Witt, 2002, pp. 26–27; A. Achleitner and E. Nathusius, 2004, pp. 8–9]

A BA is commonly classified as private person—70% of Germany's BAs are entrepreneurs themselves—that invests personal assets in privately held companies. Interestingly enough, the major motive of German BAs investing in early-stage enterprises lies in the fun of the investing activity itself, followed by the support of young entrepreneurs and the potential return of their investments. Rudolf and Witt [2002, p. 28] argue that investments of BAs commonly range from 10k to 1m Euro (and higher) per associated enterprise. Additionally, BAs provide highly valuable intangible assets such as corporate social networks or entrepreneurial knowledge. However, investors do not solely rely on gut feeling when investing in an early-stage enterprise, but rather apply investment decision-making processes to elaborate the worth of an early-stage enterprise (the reader is referred to the topic *Rules of Thumb* of subsection 2.1.2 for a more elaborate analysis). In contrast, funding by a VC is significantly more formal. [Rudolf and Witt, 2002, pp. 28–30]

VCs commonly invest in enterprises of the early- and expansion stages of the enterprise life cycle. Similar to the BA, VCs also provide intangible assets such as management activities, entrepreneurial knowledge and corporate social networking in addition to venture capital. However, the valuation process of the desired early-stage enterprise is considerably more formal compared to the investment decision-making processes of the BA. In order to valuate an enterprise, a VC traverses four stages, that is, the *initial general review*, *initial contact*, *due diligence* and *negotiation*. During the initial general review, the VC conducts checks (such as qualification of the management team or the fit of the industry sector into the VC's portfolio) based on the business plan of the enterprise. Rudolf and Witt [2002, p. 32] argue that over 90% of the enterprises get rejected in the course of the initial general review. Once a business plan of an enterprise successfully passes the initial general review, a more sophisticated inspection of the business plan is performed (including several meetings between the entrepreneurs and the VC) and—if successful—the *letter of intent*—an artefact of intentional agreement—is drawn up. Subsequently, the due diligence phase starts by valuating the enterprise at a considerably high level of detail. Finally, the negotiation phase marks the decision whether the VC agrees to invest in the corresponding enterprise. The worth of the enterprise and subsequently, the size of the VC's enterprise share, originate from the valuation result (due diligence phase). [Rudolf and Witt, 2002, pp. 30–33]

Business Incubators and -Accelerators are organizations with the aim of educating entrepreneurial skills. The goal of business incubators is the training and education of innovative project teams in order to strengthen their position and possibly enable the foundation of an early-stage enterprise [Mansano and Pereira, 2016, p. 26; Cohen, 2013, p. 19]. Cohen [2013, p. 20] argues that non-profit- and university incubators dominate the incubator landscape. Accelerators, in contrast, exhibit a different approach better expressed as *disciplining*. Whereas incubators try to shield innovative teams from the outside market's dynamics, accelerators train these teams by pushing them in at the deep end and therefore, they boost interactions with the outside market in order to make them learn more quickly [Cohen, 2013, p. 21]. The difference in their approaches can also be investigated in the corresponding incubation- or acceleration times. The average time period an incubator utilizes to educate innovative teams is commonly stated as one to five years. Accelerators, in turn, ordinarily set the training time frame to about three months, forcing *accelerated* teams to address a considerably large amount of work in a short period of time. As a consequence, codependencies within the team are being reduced to a minimum [Cohen, 2013, p. 21]. For a more detailed- and summarized representation of the distinction between incubators, accelerators and business angels, the reader is referred to Table 2.2.

Table 2.2: Characteristics of incubators and accelerators. Distinction to business angels, based on Cohen [2013, p. 20].

	Incubator	**Accelerator**	**Business Angel**
Duration	One to five years	Three months	Ongoing
Cohorts	No	Yes	No
Business Model	Rent, non-profit	Investment, non-profit	Investment
Selection	Non-competitive	Competitive, cyclical	Competitive, ongoing
Enterprise Stage	Early- and later stage	Early stage	Early stage
Education	Human resources, legal, ad hoc	Seminars	None
Mentorship	Minimum, tactical	Intense, external mentors, self	By investor (as needed)
Enterprise location	On site	On site	Off site

In conclusion, Figure 2.2 summarizes all the mentioned funding stakeholders arranged to the enterprise's life cycle.

In order to elaborate the optimal amount of venture capital allocation for an investment and subsequently, deciding on the question whether an investment is generally profitable or not,

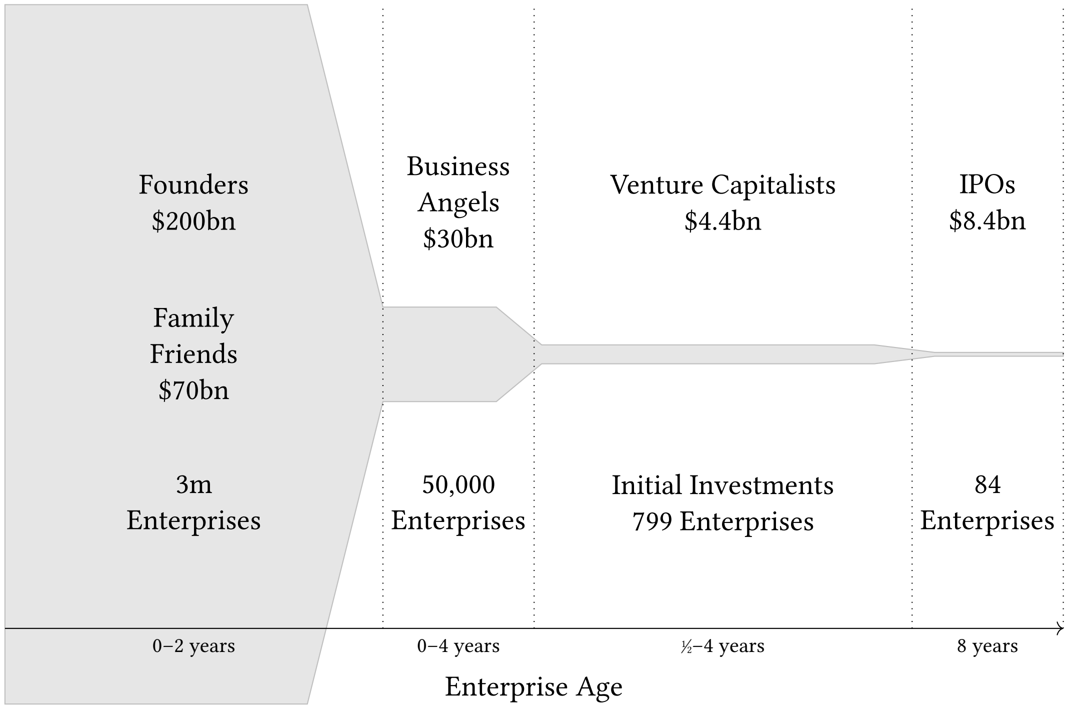

Figure 2.2: Funding levels and stakeholders arranged to enterprises' life cycle stages.

Source: Based on Bygrave and Zacharakis [2009, p. 185]

investors need the correct tools and techniques to *rate* early-stage enterprises. Subsection 2.1.2 gives a brief introduction to venture valuation techniques, elaborates on a set of venture valuation methods and introduces the reader to commonly applied investment decision-making processes.

2.1.2 Venture Valuation

According to Meyer and Bloech [2006, p. 25], *venture valuation*[6] is the process of calculating the enterprise value of an enterprise based on its future benefit to the owners of the enterprise. The general concept of the *enterprise value* is based on the fundamental aspects of economics, that is, infinite human demand in association with the scarcity of resources required for needs satisfaction. Therefore, modern venture valuation approaches orient towards generated financial surpluses and subsequently, calculate the enterprise value based on the sum of the discounted future financial surpluses [Meyer and Bloech, 2006, p. 25]. However, the worth of an enterprise calculated in the course of venture valuation invariably reflects a *relative* relation rather than a discrete value. The reason for this behaviour emerges from the fact that the process of venture

[6] Venture valuation: The term *venture* is commonly utilized in relation to the term *valuation* and therefore will be used in the course of the present paper. However, the intrinsic meaning of the terms *venture* and *enterprise* is equal.

valuation compares the utility of the valuation subject against alternative types of investments (such as the acquisition of a different enterprise or fonds). Subsequently, the final valuation of the valuation subject is based on the enterprise value of the peer enterprise [Meyer and Bloech, 2006, p. 26]. After basic analysis of the internal procedure of venture valuation, the explanation of the *How?* is completed. Yet, questions about the justification of the *Why?* may arise.

According to A. Achleitner and E. Nathusius [2004, p. 18], the valuation purpose is highly dependent on the reasons for the venture valuation as well as the role being fulfilled. The reasons for the valuation of enterprises are ordinarily distinguished by the fact whether changes in details of ownership arise in the course of a financial transaction. Thus, these reasons are classified into *decision-dependent-* and *decision-independent* reasons, whereas the former applies to the case of changing details of ownership and the latter does not change the details of ownership (such as the observation of a gearing or the endorsement of credit analysis). Furthermore, decision-dependent reasons for a venture valuation are, in turn, distinguished between *dominating-* and *non-dominating* situations. If stakeholders are not allowed to enforce a change in the details of ownership, non-dominating reasons apply. Examples can be seen in the acquisition- or disposal of enterprises and the joining of company members such as VCs. Finally, reasons for the valuation of early-stage enterprises are ordinarily classified as decision-dependent, non-dominating and cover causes such as the resignation of an owner-manager or the issuing of stock options. [A. Achleitner and E. Nathusius, 2004, pp. 15–16]

In addition to the reasons of venture valuations, the valuation purpose may be characterized by the functions or tasks a valuation shall be accomplished for. This type of characterization is also referred to as the *doctrine of functions*, which decides whether the valuation is based on the *labour theory of value (LTV)* or *marginalism*, depending on the corresponding function [A. Achleitner and E. Nathusius, 2004, pp. 16–18; Stigler, 1958; Clarke, 1991]. Therefore, the definition of the valuation purpose is defined as mainly depending on the valuation task itself and independent of the valuation reason. The doctrine of functions distinguishes between *main-* and *minor functions*, whereas the former is classified into *advisory-*, *mediation-* and *argumentative functions.* The latter, in turn, is differentiated into the *balance-*, *tax-assessment-* and *contract-design functions.*[A. Achleitner and E. Nathusius, 2004, pp. 16–18] For a more detailed representation of possible combinations of the valuation scenarios and the function types according to the doctrine of functions, the reader is referred to Table 2.3.

Table 2.3: Valuation scenario / function type combinations (according to the doctrine of functions), based on A. Achleitner and E. Nathusius [2004, p. 18]

Function type		**Valuation scenario**		
		decision-dependent		decision-independent
		dominating	*non-dominating*	
Main functions	Advisory	✓	✓	×
	Mediation	✓	✓	×

To be continued…

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Function type		Valuation scenario		
		decision-dependent		decision-independent
		dominating	*non-dominating*	
	Argumentative	✓	✓	×
Minor functions	Balance	✓	✓	✓
	Tax-assessment	×	×	✓
	Contract-design	×	×	✓

Valuation Requirements of Early-stage Enterprises

Due to their nature and characteristics, early-stage enterprises expose certain requirements, venture valuation methods need to fulfil in order to being applicable for early-stage enterprise valuation. The following passages explain four requirements, that is, *future mindedness*, *modelling adequacy*, *practicability* and *acceptance* in great detail [A. Achleitner and E. Nathusius, 2004, pp. 6–8].

Future Mindedness —one major characteristic of early-stage enterprises—derives from the fact that these valuation subjects do not possess any historic track record of business activities, because the valuation subject has not participated in any yet (the reader is referred to subsection 2.1.1 for a more detailed elaboration). Subsequently, there is no significant amount of historic datasets justifying a forecasting of the early-stage enterprise's future state. Therefore, a valuation method becomes applicable to the valuation of early-stage enterprises, if the method is not solely reliant upon historic business activity datasets, but rather orients on future aspects of the valuation subject. [A. Achleitner and E. Nathusius, 2004, p. 6]

Modelling Adequacy states that relevant venture valuation methods shall be composed of the needed data and logics in order to realistically and adequately map and value key characteristics of early-stage enterprises. Therefore, the following characteristics of early-stage enterprises need to be addressed in the course of deciding about the adequacy of a venture valuation method [A. Achleitner and E. Nathusius, 2004, p. 6]:

(i) Temporary scarcity of resources

(ii) Intangible assets

(iii) Flexible reaction to dynamics of the economic market

(iv) Risk- and profit preferences of investors

(v) Upside potential vs. downside risk

(vi) Generation of loss until reaching the expansion stage of the enterprise life cycle

Practicability of a venture valuation method is classified on the basis of its complexity. Thus, venture valuation methods are practicable if the effort of its application is adequate. This constraint is fulfilled if the acquisition- and reliability of data is guaranteed. Furthermore, the corresponding valuation method needs to fulfil the requirement of transparency in order to be fully comprehensible by the stakeholders being involved in the valuation (such as the corresponding members of the contract negotiations). [A. Achleitner and E. Nathusius, 2004, p. 7]

Acceptance expresses both the theoretic- and practical relevance and importance of a venture valuation method by science and industry. However, being theoretically- or formally applicable does not imply the practical use of a valuation method by market- or industry sectors, who rather apply certain domain-specific standards or conventions in order to value enterprises. [A. Achleitner and E. Nathusius, 2004, pp. 7–8]

Classification of Venture Valuation Methods

As described earlier, venture valuation methods generally calculate the enterprise value based on certain input factors and the application of domain knowledge justifying future benefits. Due to the fact that input data and domain-logic may vary significantly upon various venture valuation methods, these techniques are usually classified into categories. According to A. Achleitner and E. Nathusius [2004, p. 26], venture valuation methods are mainly divided into *situation-specific* and *-unspecific* techniques, whereas the former addresses valuation methods specific to the reason of a valuation. These venture valuation techniques are comprised of the *total valuation methods*—characterized by but not limited to their future mindedness—and *rules of thumb* such as the *components method* or the *method of thirds*. In particular, total valuation methods include techniques such as the *venture-capital-* and *first-chicago* method. [A. Achleitner and E. Nathusius, 2004, pp. 25–26]

Situation-unspecific venture valuation methods, on the other hand, include applicable techniques that are independent of the valuation reason. Following the *classic systematization*, A. Achleitner and E. Nathusius [2004, p. 24] argue that the calculation of the enterprise value is either based on fundamental data of the enterprise being evaluated or based on data extracted from the economic market. Therefore, situation-unspecific venture valuation methods are classified into *fundamental-analytic-* and *market-oriented techniques* respectively. Whereas market-oriented techniques include venture valuation methods such as the *industry-sector-* and *peer-group multiples*, fundamental-analytical techniques are further distinguished into *single-* and *total valuation methods*. Single valuation methods (such as the *net asset value-* or *liquidation value analysis*) do not fulfil the requirement of future mindedness and are therefore not covered by the present work. The total valuation method is defined analogously to the corresponding version of the situation-unspecific venture valuation category and includes methods such as the *discounted cashflow- (DCF)*, *real-options value-* and *net value analysis*. [A. Achleitner and E. Nathusius, 2004, pp. 24–25] For a more detailed representation of venture valuation method categories, the reader is referred to Figure 2.3.

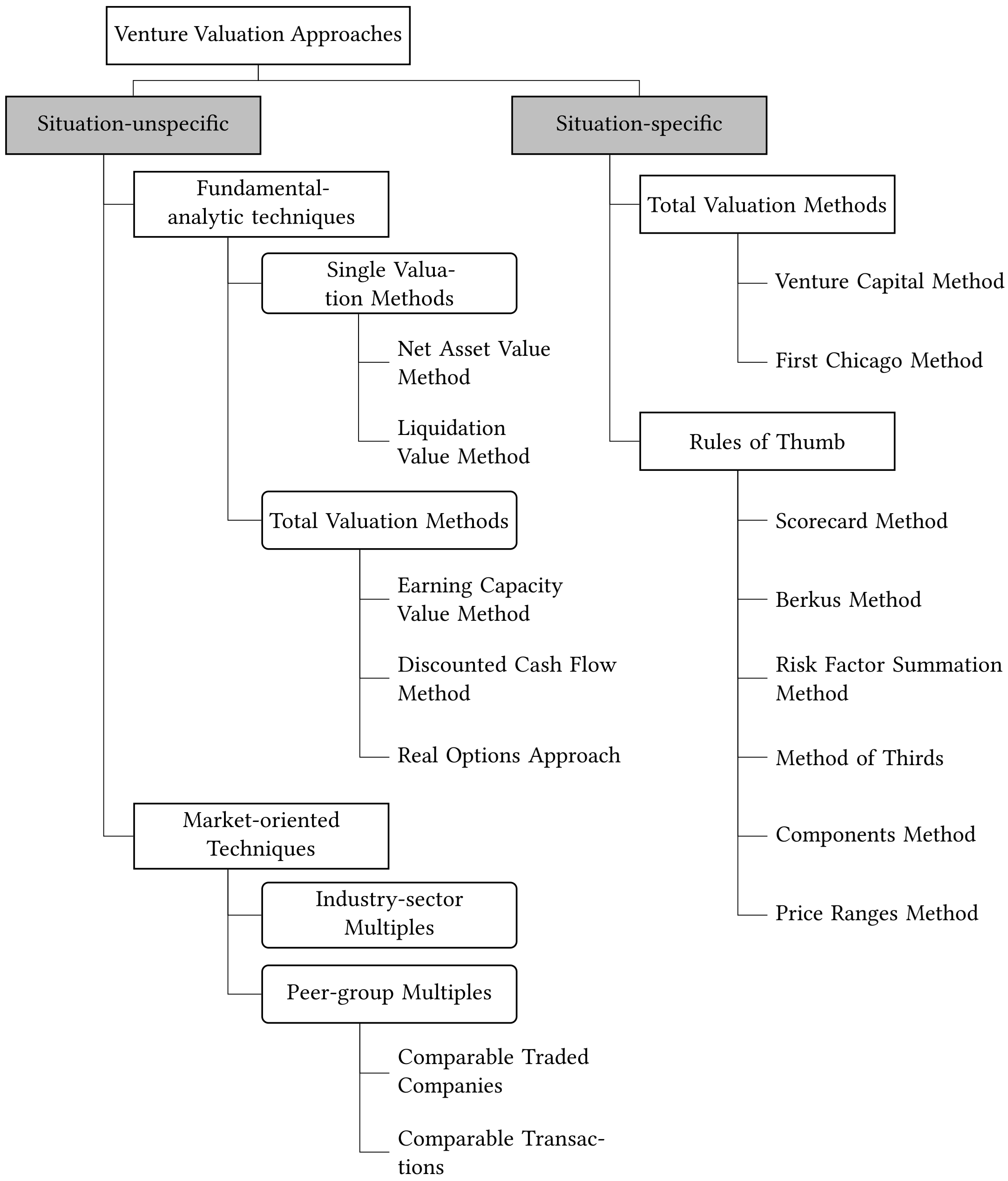

Figure 2.3: Classification of venture valuation methods

Source: Based on A. Achleitner and E. Nathusius [2004, p. 26]

In addition to the the main venture valuation method categories outlined above, valuation methods underlying venture capital financing of enterprises, are distinguished into *pre-revenue-* and *post-revenue valuations* [Rudolf and Witt, 2002, p. 33]. The difference between these valuation types lies in the calculation of the enterprise value. The pre-revenue valuation does not include the venture capital the investor is about to fund and therefore needs to be added explicitly in order to calculate the post-revenue value [Rudolf and Witt, 2002, p. 34]:

$$\textit{post-revenue value} = \textit{enterprise value} + \textit{venture-capital} \tag{2.1}$$

The post-revenue valuation, on the other hand, already includes the investor's investment sum in the enterprise value and therefore, the pre-revenue value is calculated as follows [Rudolf and Witt, 2002, p. 34]:

$$\textit{pre-revenue value} = \textit{enterprise value} - \textit{venture-capital} \tag{2.2}$$

Furthermore, the differentiation between pre- and post-revenue valuation highly affects the calculation of the equity share of the enterprise the investor is about to acquire after funding [Rudolf and Witt, 2002, p. 34]. In the case of pre-revenue valuation, the calculation of the equity-share is accomplished as follows:

$$\textit{equity share} = \frac{\textit{venture capital}}{\textit{post-revenue value}} \tag{2.3}$$

Calculating the equity-share in the case of post-revenue valuation is performed analogously:

$$\textit{equity share} = \frac{\textit{venture capital}}{\textit{pre-revenue value} + \textit{venture capital}} \tag{2.4}$$

The aim of the upcoming topic lies in the detailed description of (types of) venture valuation methods.

Venture Valuation Methods

The present passage introduces and analyses venture valuation methods already addressed in subsection 2.1.2. The investigated methods provide the basis for the methodology (see section 2.2) of the present work. The reader is referred to Figure 2.3 for a detailed classification of the following venture valuation methods.

Net Asset Value- and Liquidation Value Method The net asset value- and liquidation value method both belong to the domain of single valuation methods and basically calculate the enterprise value by summation of the worth of enterprise assets [Rudolf and Witt, 2002, p. 55]. The problem of these methods may be seen in the fact that each of them is not capable of fulfilling the requirement of future mindedness and therefore, these methods are not applicable to the valuation of early-stage enterprises [A. Achleitner and E. Nathusius, 2004, p. 25]. As a consequence, the present work will not cover the net asset value- and the liquidation value methods.

Earning Capacity Value Method Classified as total valuation method of the situation-specific valuation techniques, the earning capacity value method is based on the investment methodology of the capital value. This method aims at calculating the enterprise value based on the enterprise's future discounted net payments to the shareholders, because the income return of a shareholder's investment is solely dependent on net payments from the valuation subject. Net payments, in turn, are composed of dividends and the increase of the share price. Subsequently, an investor only receives dividends or net withdrawals as constant payments (except selling share). The core element of the earning capacity value method is stated as the *earning-capacity value*. [Rudolf and Witt, 2002, pp. 59–60]

The earning-capacity value EV is based on the summation of the after-tax dividends D_t and the discounted net withdrawals respectively, annually redeemed by the enterprise to the shareholders [Rudolf and Witt, 2002, pp. 60–61], more formally:

$$EV = \sum_{t=1}^{\infty} \frac{D_t}{(1+r)^t} \tag{2.5}$$

where

$$r \ldots \textit{calculatory interest rate} \qquad t \ldots \textit{time index}\ .$$

As addressed in Equation (2.5), discounting of future net payments is conducted utilizing a calculatory interest rate r corresponding to the income return of the best alternative investment type (such as investment fonds, stocks or the investment in a different enterprise). Rudolf and Witt [2002, p. 62] argue that—in practice—it is impossible to know all investment alternatives at the time of valuation. Subsequently, determining the best alternative investment is not feasible, if calculated ex post. Thus, the best practice of determining r is the utilization of a *country-specific-* or *risk-adjusted capital market interest rate* [Rudolf and Witt, 2002, p. 62].

The calculation of a risk-adjusted capital market interest rate can be accomplished by the utilization of capital market models such as the internationally recognized *capital asset pricing model (CAPM)* [Rudolf and Witt, 2002, p. 76; Sharpe, 1964; Fama and French, 2004]. These models determine the calculatory interest rate on the basis of the income return—demanded by the market—of a peer investment of the same risk class as the enterprise of interest. More formally, the calculation of the calculatory interest rate r_{EC} for the valuation of an equity-financed enterprise —the cost of equity financing in the context of the income return demanded by the shareholders—is derived as follows [Rudolf and Witt, 2002, p. 76; A. Achleitner and E. Nathusius, 2004, p. 47]:

$$r_{EC} = r_f + \beta(r_M - r_f) \tag{2.6}$$

where r_f is stated as the *riskless interest rate*, β defines the *risk class* of the valuated enterprise's stocks and r_M expresses the market return. The calculation of β may only be accomplished if the valuated enterprise is publicly listed on the stock exchange. If not, the general best practice is the utilization of the β values of comparable enterprises listed on the stock market [Rudolf and Witt, 2002, p. 77]. However, the valuation of early-stage enterprises requires a more elevated calculatory model as the basis of the earning capacity value.

Due to the fact that early-stage enterprises are liable to high dynamics especially in the early stages of the enterprise life cycle (see subsection 2.1.1), the earning capacity value method needs to be adapted in order to model these dynamics. Therefore, the following domain knowledge needs to be applied in the form of business rules [Rudolf and Witt, 2002, pp. 67–68]:

(i) The first stage of an enterprise is scarred by loss and therefore, there is no distribution of profit until time n.

(ii) The enterprise generates profit D_1 with a growth rate g —modelling competitive advantage—until time $n + m$.

(iii) The final phase—starting at $n + m + 1$ until infinite time—of the enterprise's life cycle is determined by the generation of normal profit D_2 without a growth rate.

More formally, the updated calculation model of the earning capacity value is stated as follows [Rudolf and Witt, 2002, p. 68]:

$$EV = \sum_{t=n+1}^{n+m} \frac{D_1(1+g)^{t-(n+1)}}{(1+r)^t} + \sum_{t=n+m+1}^{\infty} \frac{D_2}{r(1+r)^t} \tag{2.7}$$

In summary, the earning capacity value method was one of the first (and only) valuation methods accepted by the *Main Specialist Committee* of the *Institut der Wirtschaftsprüfer* in Germany [Rudolf and Witt, 2002, pp. 59–60; Institut der Wirtschaftsprüfer in Deutschland, 2008]. In addition to the earning capacity value method, another total valuation method got accepted as well: The discounted cash flow method [Institut der Wirtschaftsprüfer in Deutschland, 2008].

Discounted Cash Flow Method (DCF) The DCF method is a venture valuation method that is based on the future cash flows of an enterprise [A. Achleitner and E. Nathusius, 2004, pp. 29, 39]. Cash flows are defined as the means of payment utilized between the valuated enterprise and its stakeholders such as customers or suppliers. The central decision criterion of the DCF analysis on the valuation of an enterprise lies in the question whether the corresponding enterprise is capable of generating positive future cash flows. However, there exist several types of cash flows that are explained in detail as follows [A. Achleitner and E. Nathusius, 2004, pp. 30, 31]:

(i) Operative cash flow: Cash in- and outflows[7] from operational business.

(ii) Free cash flow: Operative cash flow deducted by investments in tangible- or other assets and increased by negative investments[8]. The free cash flow is also referred to as the flow-to-entity that belongs to investors.

[7]Cash in- and outflows define deposit- and disbursal respectively in the corresponding business period.

[8]Negative investments define the process of transforming tangible- into financial assets (such as disposal).

(iii) Cash flow to equity investors: Deducting interest payments, clearance of debt to external capital providers and payments to non-proprietors of the enterprise from the free cash flow yield the cash flow to equity investors, also referred to as flow-to-equity.

In the course of the DCF analysis, forecasts of future cash flows are based on the analysis of historic market dynamics as well as the free cash flow and cash flow to equity investors of the valuated enterprise. Therefore, the structure of the enterprise's deposits and disbursals are being determined in the course of the cost- and activity accounting. Based on this historic data analysis, predictions on future cash flows may be implied. However, this very fact results in a considerably large problem for early-stage enterprises. [A. Achleitner and E. Nathusius, 2004, p. 31]

Due to the fact that most early-stage enterprises do not posses any historic business activity datasets, forecasting is highly inaccurate or entirely impossible. Additionally, cash flows—if already generated—may be misleading because of their negativity especially in the early stages of the enterprise and therefore, these cash flows are not representative as basis for the predictions of development. Examples of these conditions may be seen in considerably large initial investments, evolution in the business plan or changing dynamics of the economic environment. In order to address these problems, the DCF method needs to fully model the emerging dynamics. [A. Achleitner and E. Nathusius, 2004, pp. 31–32]

The DCF analysis is distinguished into two approaches, that is, the *equity*- and *entity approach* [Rudolf and Witt, 2002, p. 79]. The former is based on payments of the valuated enterprise to the shareholders and is therefore almost equal to the earning capacity value method discussed in subsection 2.1.2 (the only possible difference lies in the calculation of the calculatory interest rate, if the earning capacity value method utilizes country-specific interest rates instead of the CAPM). In order to calculate the *net cash flow*—also referred to as NCF —the payment to the shareholders are discounted periodically by the utilization of a risk-adjusted equity capital interest rate r_{EC}. Subsequently, the generic calculation of the enterprise value $DCFV^{net}$ is conducted as follows [Rudolf and Witt, 2002, p. 80]:

$$DCFV^{net} = \sum_{t=1}^{\infty} \frac{NCF_t}{(1 + r_{EC})^t} \tag{2.8}$$

In order to model the dynamics of early-stage enterprises, Rudolf and Witt [2002, p. 81] propose the utilization of a three-phase model analogously to the earning capacity value method (that is $0 \ldots n$, $n + 1 \ldots m$, $m + 1 \ldots \infty$) and a growth rate g of the net cash flows . More formally, the enterprise value is calculated as follows:

$$DCFV^{net} = \sum_{t=n+1}^{n+m} \frac{NCF_1}{(1 + g)^{t-(n+1)}} + \frac{NCF_2}{r_{EC}(1 + r_{EC})^{n+m+1}} \tag{2.9}$$

Finally, the entity approach—the second type of the DCF methods—is based on payments to *all* investors. Therefore, in contrast to the equity approach, the entity approach also includes interest payments to creditors. Subsequently, the enterprise value represents the total value of the enterprise in the context of all stakeholders (as opposed to the equity method's context of equity investors). More formally, the entity approach calculates the enterprise's total value by the utilization of all investors' future after-tax gross cash flows (BCF), that is, periodical payments to equity- and external investors. In order to calculate the final enterprise value $DCFV^{gross}$, these payments need to be discounted by the cost of capital c and deducted by the market value of the debt capital DC [Rudolf and Witt, 2002, pp. 83–84]:

$$DCFV^{gross} = \sum_{t=1}^{\infty} \frac{BCF_t}{(1+c)^t} - DC \tag{2.10}$$

The cost of capital c is calculated according to the *weighted average cost of capital (WACC)* that gives —as a fact of its US origin—tax incentives in the form of the deductibility of debt capital interest rates. Subsequently, this circumstance reduces the cost of external capital (also referred to as *tax shield*). At a flat tax rate s, cost of capital calculation according to WACC is defined as follows [Rudolf and Witt, 2002, pp. 84–85; A. Achleitner and E. Nathusius, 2004, p. 55]:

$$k_{WACC} = r_{EC}\frac{EC}{EC+DC} + r_{DC}(1-s)\frac{DC}{EC+DC} \tag{2.11}$$

where EC defines equity capital, DC conforms to external/debt capital and r_{EC} / r_{DC} map the cost of equity- and external/dept capital respectively.

Real Options Approach Based on the DCF analysis, the real options approach financially valuates explicitly defined entrepreneurial scopes that may be utilized by enterprise owners in the future. As a consequence, the enterprise value is distinguished into two parts, that is, the *passive*- and the *active enterprise value*. Whereas the former defines option-free value components that are valuated utilizing the DCF method, the latter expresses option-like value components that are determined in the course of the application of option pricing models. Subsequently, the major advantage to the DCF analysis emerging from these facts can be seen in the high flexibility of the management team to act according to changing economic environmental dynamics (as opposed to the DCF method that utilizes a constant discounting interest rate to model theses dynamics). However, quantifying the various entrepreneurial scopes within an enterprise, irreversibility of investments, insecurity of entrepreneurial scopes and the considerably high complexity of option pricing models in general, highly impede the application of the real options approach. [A. Achleitner and E. Nathusius, 2004, pp. 67, 71, 74, 75]

The valuation of an enterprise in the course of the real options approach basically consists of two phases, that is, the identification of real options within the enterprise and the conduction of the valuation. In order to identify real options, a strategic analysis of the enterprise with the assistance of the real options' classification scheme depicted in Figure 2.4 needs to be performed.

Real options are generally divided into *strategic*-, *operative*- and *financial options*. Strategic options constitute the *worth* of flexibility of conducting future investments or disinvestments.

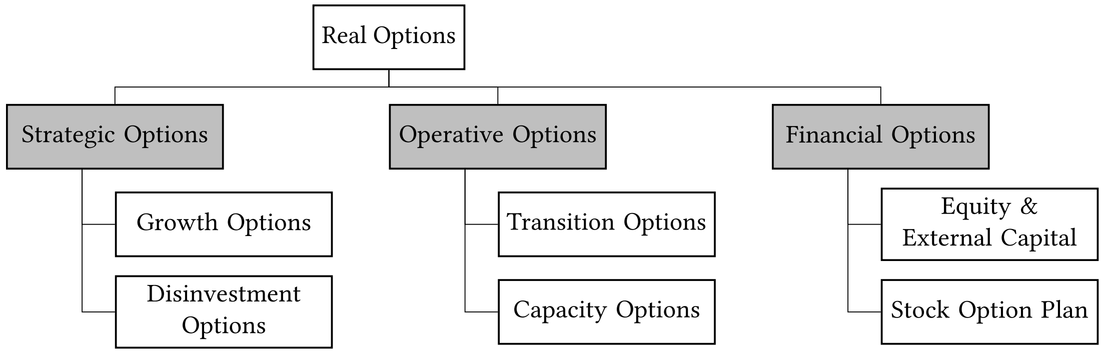

Figure 2.4: Classification of real options

Source: Based on Meyer and Bloech [2006, p. 169]

Whereas the former is classified as *growth option*, the latter belongs to the domain of *disinvestment options*. As a consequence, both strategic- and operative real options are based on the service area of the enterprise's assets. Operative options, on the other hand, are based on the flexibility of optimized asset utilization, subsequently leading to optimal enterprise resource management. Therefore, operative options are distinguished into *transition-* and *capacity options*. Finally, financial options describe certain liabilities (such as equity capital in stocks or external capital) on the enterprise's balance sheet. [Meyer and Bloech, 2006, pp. 169–170]

As already mentioned, the real options method utilizes option pricing models in order to valuate an enterprise. These models are basically distinguished between *numerical-* and *analytical* techniques. Numerical option price models are based on the approximated resolution of a problem rather than its formal solution. The approximation is generally conducted in the course of the following approaches [A. Achleitner and E. Nathusius, 2004, pp. 81–82]:

(i) Transformation of differential equations of value amendment equations into discrete differential equations that, in turn, are approximated utilizing backward induction.

(ii) Approximation of stochastic processes.

The latter is utilized in procedures such as the *Monte-Carlo simulation* and *lattice approaches*. Monte Carlo simulations in the context of option pricing models are ordinarily specified for every value driver, whereas the corresponding probability distributions are elaborated utilizing empirical surveys. Thereafter, simulation runs based on this data are conducted applying randomly chosen value drivers with the aim of delivering an option price per simulation run. The probability distribution of the option price is methodically collected after a considerably large amount of simulation runs have passed. Finally, the corresponding option price of the highest probability is selected as the solution. [A. Achleitner and E. Nathusius, 2004, pp. 82–83; Metropolis and Ulam, 1949]

Lattice approaches, in turn, visualize and calculate value adjusting processes of the underlying assets in the course of *lattice trees* that are based on the event tree of the underlying asset. Starting at the terminal nodes of the event tree, recursive checks calculate the success of an investment for the current point in time. The solution is the optimal investment date maximizing success. The most famous model of the lattice approach is the *binomial model of Cox/Ross/Rubinstein.* [A. Achleitner and E. Nathusius, 2004, pp. 82–83; Cox, Ross, and Rubinstein, 1979]

Analytical techniques—the second type of option price models—calculate the solutions of economic problems in the course of exact- or analytical formulae, depending on the corresponding approach. Straightforwardly structured options may provide exact —which is also referred to as *closed*—solutions that visualize the value amendment of the base object as continuous, stochastic process in the form of an equation. Subsequently, this equation is partially differentiated in order to map the duplicate portfolio. Finally, the resulting differential equations are solved according to the option's worth and under consideration of second-order conditions. The *model of Black/Scholes* is the most common analytical option pricing model. [A. Achleitner and E. Nathusius, 2004, pp. 82–83; Black and Scholes, 1973]

Multiples Multiples define a venture valuation approach of the domain of market-oriented techniques that exploits market prices of established comparable peer enterprises or industry sectors in order to infer the enterprise value of the valuation subject [A. Achleitner and E. Nathusius, 2004, p. 115]. The corresponding data that is being compared in the course of the valuation is stated as so called *key performance indicators (KPI)* (such as profit or revenue) of the enterprise. Market-oriented valuation techniques are based on the supposition that the market-price/KPI ratio—which is expressed by a factor, the so called *multiple*—is similar to ventures of the same domain or industry sector. Therefore, the enterprise value of the valuated enterprise is determined by multiplying the KPI and the corresponding multiple. [A. Achleitner and E. Nathusius, 2004, p. 115]

However, the main model of the multiples approach is based on the hypothesis of capital market equilibrium[9], constant risk preference among all market participants and total allocation- and information efficiency respectively. Subsequently, the calculated market price is derived from all available resources implying an objective value. Nevertheless, the mentioned constraints only exist in theory and therefore, the valuation under *perfect* conditions is not feasible. [A. Achleitner and E. Nathusius, 2004, pp. 115–116] Subsequently, market-oriented valuation techniques may be classified as approximations rather then exact formulae.

The approximation of the enterprise value in the course of market-oriented techniques is distributed into two types of multiples, that is, *industry sector-* and *peer group multiples.* The former type is estimated by experts of the domains of investment banking, accounting/auditing and business consultancy. An alternative approach lies in the assessment of industry sector/stock multiples based on the analysis of the stock exchange [Finance, 2017a]. Table 2.4 visualizes an

[9] A capital market equilibrium emerges when (i) all market participants have access to arbitrary amounts of capital at a unified interest rate, (ii) transactional costs and taxes do not exist, (iii) market participants suppose the uncontrollability of interest rates, (iv) the capital market is of competitive nature, (v) expectations of market participants are homogeneous [Rudolph, 2006, pp. 28–29]

excerpt of industry sector/stock- and expert EBIT[10]/revenue multiples of September/October 2017. The calculation of the market value of an enterprise on the basis of a certain KPI according to industry sector/stock multiples is conducted as follows [based on A. Achleitner and E. Nathusius, 2004, p. 126]:

$$MV_{i,TE} = M_{KPI_i} \cdot KPI_{i,TE} \tag{2.12}$$

where $MV_{i,TE}$ is stated as the market value of the target enterprise TE under the context of KPI i, M_{KPI_i} is specified as the multiple based on KPI i and $KPI_{i,TE}$ is defined as the utilized KPI i of the target enterprise TE.

Table 2.4: Industry sector/stock- and expert EBIT/revenue multiples excerpt of September/October 2017, based on Finance [2017b, pp. 88–89]

Industry sector	**Stock multiples**		**Expert multiples (Small-Cap[11])**			
	EBIT	Revenue	EBIT		Revenue	
			from	to	from	to
Software	14.70	1.88	7.70	9.90	1.32	1.79
Telecommunication	15.00	1.67	7.60	9.50	0.92	1.27
Trading & E-Commerce	11.70	0.77	6.50	9.00	0.60	0.90
Media	11.40	2.15	6.70	8.90	0.91	1.52
Transp., Logistics & Tourism	12.50	1.09	6.00	8.00	0.50	0.80
Machinery- & Plant Eng.	15.20	1.28	6.90	8.80	0.70	0.97
Env. Techn. & Renew. Energy	—	—	6.60	8.60	0.70	1.00
Constructions & Crafts	14.70	1.14	5.50	7.50	0.50	0.77
Pharmaceutical industry	12.20	1.83	8.00	10.3	1.41	1.97
Electrical Eng. & Electronics	14.50	0.99	6.50	8.60	0.70	1.00
Gas, Electricity & Water	13.00	0.79	6.00	7.60	0.68	1.00

The main idea of peer group multiples—the second type market-oriented valuation techniques—is based on the procedure of finding comparable enterprises—the peer group—that already expose market values. Subsequently, unified multiples are calculated among the peer group that, in turn, are utilized to determine the market value of the target enterprise. In general, the literature discusses two types of multiples depending on the peer groups, that is, *comparable traded companies*- and *comparable transactions multiples*. Whereas the former multiple type is calculated based on the comparison of enterprises listed on the stock exchange, comparable transactions multiples are utilized if the comparison is based on market prices. [A. Achleitner and E. Nathusius, 2004, pp. 122–123] However, the process of applying peer group multiples is independent of the multiple's type.

The process of valuating a target enterprise in the course of peer group multiples may be distinguished into the following steps [based on A. Achleitner and E. Nathusius, 2004, p. 124]:

[10]Earnings before interests an taxes (EBIT) is a KPI that is calculated by the cumulation of revenue and other operating income and the subtraction of depreciation of tangible and intangible assets, material-, personnel- and other operating expenses [A. Achleitner and E. Nathusius, 2004, p. 34]

[11]Small-Cap: Enterprises whose revenue is smaller than Euro 50m per year

(i) Analysis of the target enterprise by conducting qualitative- and quantitative research. Information about the enterprise (such as management factors, the enterprise's market share, profitability- and liquidity KPIs) is determined.

(ii) Identification of the peer group (enterprises) based on key information of the target enterprise.

(iii) Calculation of the target enterprise's market value. This process includes the determination of the peer group's market values, KPIs and the calculation of the average multiple needed for the valuation of the target enterprise.

Identifying the peer group is mainly conducted by filtering enterprises based on the target enterprise's industry sector. Subsequently, enterprises are added to the peer group, if the similarity to the target enterprise in terms of the chosen KPIs is considerably high. The next step is considered to be the determination of the KPI the final multiple shall be based on (for instance profit or revenue). After choosing the appropriate KPI, the unified multiple among the peer group is calculated as follows [based on A. Achleitner and E. Nathusius, 2004, p. 125]:

$$\frac{MV_{TE}}{KPI_{i,TE}} = \frac{\sum_{v=1}^{V} \frac{MV_v}{KPI_{i,v}}}{V} = M_{TE_i} \tag{2.13}$$

where V is stated as the size of the set of comparable enterprises (the peer group), MV_v and $KPI_{i,v}$ are defined as the market value KPI i of the comparable enterprise v respectively. Utilizing M_{TE_i}, the final market value of the target enterprise TE is calculated analogously to Equation (2.12). However, considering early-stage enterprises as subject of valuation, more sophisticated formulae of the peer-group multiple calculation than mentioned in Equation (2.13) need to be determined.

Valuation of early-stage enterprises in the course of the multiples valuation approach is a non-trivial task, due to early-stage enterprise's unique characteristics such as non-existent historical track records of business activities, non-existent revenue, profit and positive cash flows, only to mention a few. As a consequence, early-stage enterprises barely expose any KPIs sophisticated enough to suffice for the application in the valuation process. For this reason, *future-oriented multiples* may be seen as an alternative to the classical multiples approaches. [A. Achleitner and E. Nathusius, 2004, p. 135]

Future-oriented multiples are mainly distributed into the following approaches:

(i) Current multiples are utilized to calculate the future enterprise value based on the enterprise's expected KPI. This approach may be seen as an approximation of the future enterprise value due to the fact that the theoretic construct of multiples being independent of time, which does not hold in reality. Finally, the calculated future enterprise value needs to be further discounted (by means such as the WACC or equity costs). The following equation visualizes the calculation more formally [based on A. Achleitner and E. Nathusius, 2004, p. 136].

$$MV_{TC,TE} = \frac{\sum_{v=1}^{V} \frac{MV_{TC,v}}{KPI_{EnV,v,0}}}{V \cdot (1 + k_{WACC})^t} \cdot KPI_{EnV,TE,t} \tag{2.14}$$

where $MV_{TC,TE}$ is stated as the market value of the total capital of the future enterprise value, $KPI_{EnV,TE,t}$ is defined as the enterprise value KPI of the target enterprise at time t, $MV_{TC,v}$ is stated as the market value of the total capital of the comparable enterprise v, $KPI_{EnV,v,0}$ is determined as the enterprise value KPI of the comparable enterprise v at the time of valuation, V is specified as the size of the set of comparable enterprises (the peer group) and k_{WACC} is defined as the weighted average cost of capital (the reader is referred to the *Discounted Cash Flow Method (DCF)* passage for a more detailed explanation).

(ii) Utilization of the expected KPIs of the peer group: In contrast to the previous approach, this procedure does not calculate the future enterprise value but rather the expected references for the determination and application of the corresponding multiple are gathered. Discounting is not needed. However, the corresponding KPIs of the enterprises in the peer group are required but commonly not available. Therefore, these KPIs need to be estimated from former growth rates, leading to a possible forecasting problem. Referring to Equation (2.14), the following equation visualizes the calculation more formally [based on A. Achleitner and E. Nathusius, 2004, p. 137].

$$MV_{TC,TE} = \frac{\sum_{v=1}^{V} \frac{MV_{TC,v}}{KPI_{EnV,v,t}}}{V} \cdot KPI_{EnV,TE,t} \tag{2.15}$$

where $KPI_{EnV,v,t}$ is determined as the enterprise value KPI of the comparable enterprise v at time t. The variables are defined analogously to Equation (2.14).

Total Valuation Methods The group of *total valuation methods* belongs to the domain of situation-specific valuation methods. Analogously to rules of thumb—the second type of situation-specific valuation methods—total valuation methods are only applicable in the course of venture capital financing based on a specific valuation reason. The most commonly utilized total valuation methods are the *venture capital-* and the *first chicago method* that are being analysed in the following passages.

The Venture Capital Method —which is also referred to as *fundamental pricing method*—is an easily applicable valuation analysis due to its simplistic economic presumptions and therefore, this method mostly is not covered in scientific literature [A. Achleitner and E. Nathusius, 2004, pp. 1145–146]. However, due to its popularity in the industry and the principle of completeness, the present work depicts this method in detail. The main aspect of the venture capital method lies in the fact that it is biased towards the investor's endeavour to maximize profit at the disposal of enterprise shares. As a consequence, dividend distribution has less emphasis on the valuation process or is disregarded respectively. Furthermore, a major constraint of the venture capital method is specified as the assumption of a projected success of the valuation subject. In addition to the calculation of the enterprise's future value and subsequently, the computation of the present value, the venture capital method determines the required enterprise share the venture capitalist needs to demand. Finally—after the compensation of diluting effects—the price of the shares to be issued, is determined. The following enumeration depicts the valuation process in more (formal) detail [A. Achleitner and E. Nathusius, 2004, p. 147]:

(i) Estimation of the future enterprise value: The most important aspect of calculating the future value is the determination of the enterprise's exit date, which is dependent on factors that include but are not limited to the corresponding characteristics of the enterprise or industry sector and is ordinarily stated as five year time period. The calculation of the future value is formally conducted in the course of a separate venture valuation method. A. Achleitner and E. Nathusius [2004, p. 148] argue that multiples and simplified forms of the DCF approach are commonly utilized due to their straightforward application. Equations (2.16) and (2.17) show the formulae based on the multiples- and the DCF approaches respectively [based on A. Achleitner and E. Nathusius, 2004, pp. 149–150].

$$FV_T = M_{KPI_{i,0}} \cdot KPI_{TE,T} \quad (2.16)$$

$$FV_T = \frac{CFEC_{T+1}}{r_{EC}} \quad (2.17)$$

where FV_T is defined as the future value at time of exit T, $M_{KPI_{i,0}}$ states the multiple based on KPI i at valuation time ($t = 0$), $KPI_{TE,T}$ determines KPI i of the target enterprise TE at time of exit T, $CFEC_{T+1}$ defines the cash flow to the shareholders in period T and r_{EC} states the equity costs.

(ii) Estimation of the present value: In the course of discounting the future value, the present value is calculated utilizing an income return r including the venture capitalist's risk level. The calculation itself is classified as post-revenue valuation due to the fact that the venture capitalist's investment sum and commitment is already comprised in the valuation—$PV_{0,Post}$. The determination of the pre-revenue valuation of the present value at time 0—$PV_{0,Pre}$—is conducted by subtracting the investment sum I from the post-revenue valuation $PV_{0,Post}$. More formally, the pre- and post money valuations $PV_{0,Post}$ and $PV_{0,Pre}$ respectively, are calculated as follows [based on A. Achleitner and E. Nathusius, 2004, pp. 151,152]:

$$PV_{0,Post} = \frac{FV_T}{(1+r)^T} \quad (2.18)$$

$$PV_{0,Pre} = PV_{0,Post} - I \quad (2.19)$$

where $PV_{0,Post}$ and $PV_{0,Pre}$ specify the pre- and post-revenue valuations of the present value at time 0 respectively.

(iii) Calculation of the required enterprise share: Dividing the venture capitalist's investment sum by the post-revenue valuation of the present value determines the required enterprise share ES, more formally [based on A. Achleitner and E. Nathusius, 2004, p. 152]:

$$ES = \frac{I}{PV_{0,Post}} \tag{2.20}$$

(iv) Compensation of delusive effects (optional): If the venture capitalist knows that further investment rounds are needed at the time of valuation, the present calculation step is required in order to compensate the shift in enterprise shares induced by the variation in the amount of shareholders (otherwise, this step is not necessary). The extent of the compensation of these diluting effects—also referred to as retention rate RET—is calculated by the summation of the final enterprise share $ES_{T,m}$ at exit time T of every future venture capitalist m causing delusion effects. Furthermore, the retention rate RET in the context of the current investor may be defined as the division of the enterprise share ES_T at exit time T and the required enterprise share ES_0 at time of valuation ($t = 0$). More formally, the final equity share of the current venture capitalist at valuation time incorporating delusive effects is determined as follows [based on A. Achleitner and E. Nathusius, 2004, p. 155]:

$$RET = 1 - \sum_{m=1}^{M} ES_{T,m} = \frac{ES_T}{ES_0} \Leftrightarrow ES_0 = \frac{ES_T}{1 - \sum_{m=1}^{M} ES_{T,m}} \tag{2.21}$$

(v) Price of the shares to be issued: Finally, the amount of new shares NS and subsequently, the price of these shares P_{NS} is based on the amount of already existing shares OS, the venture capitalist's investment sum I and the required enterprise share ES_0 at valuation time ($t = 0$). Equations (2.22) and (2.23) show the formulae in more detail [based on A. Achleitner and E. Nathusius, 2004, p. 156].

$$NS = OS \cdot \frac{ES_0}{1 - ES_0} \tag{2.22}$$

$$P_{NS} = \frac{I}{NS} \tag{2.23}$$

The First Chicago Method —the second valuation analysis of the domain of total valuation methods—differs from the venture capital method in the fact that instead of only assuming the success of an enterprise, several scenarios for the worst-, base- and best cases are considered in the course of the venture valuation process. In contrast to the fundamental pricing method, the first chicago method considers—in addition to the capital reflux at the time of the enterprise's exit, —disbursements of dividends to investors before the disposal of the enterprise in the valuation process [A. Achleitner and E. Nathusius, 2004, p. 173]. As a consequence, lower interest rates are utilized due to the elimination of target figures because of the multi-scenario valuation. Furthermore, the valuation process is based on the expected cash flow to the investors, which, in turn, is defined as the weighted average of worst-, base- and best case scenarios. The valuation scenarios themselves are constrained to subjective occurrence probabilities. [A. Achleitner and E. Nathusius, 2004, pp. 172–173]

The first chicago method is composed of the following constraints and definitions: $unspCFVC_{t,-}$, $unspCFVC_{t,0}$ and $unspCFVC_{t,+}$ specify the exit-unspecific cash flows to investors in the worst-, base- and best cases respectively. The required enterprise share ES is based on the investment's worth $FV_{I,T}$ at the time of exit T, built on the best case scenario. The occurrence probabilities of the valuation scenarios (worst-, base- and best cases) are defined as p_-, p_0 and p_+ respectively. The target return is stated as r. More formally, FV_T is specified as the investment sum I compounded by the target return and specified as follows [based on A. Achleitner and E. Nathusius, 2004, p. 173]:

$$FV_{I,T} = I \cdot (1+r)^T \tag{2.24}$$

This investment terminal value is generated in the course of exit, paid to the investor and therefore matches the compounded expected cash flow to the investor, more formally [based on A. Achleitner and E. Nathusius, 2004, p. 174]:

$$FV_{I,T} = FV_{CFVC,T} \tag{2.25}$$

$FV_{CFVC,T}$, in turn, is composed of the terminal value of the exit-unspecific- and exit-specific cash flows $FV_{unspCFVC,T}$ and $FV_{spCFVC,T}$ in the best case scenario [based on A. Achleitner and E. Nathusius, 2004, p. 174]:

$$FV_{CFVC,T} = FV_{unspCFVC,T} + FV_{spCFVC,T} \tag{2.26}$$

The terminal value of the exit-unspecific cash flows is determined based on the compounded cash flows of the different scenarios weighted by their occurrence probabilities, more formally [based on A. Achleitner and E. Nathusius, 2004, p. 174]:

$$\begin{aligned} FV_{unspCFVC,T} = p_- &\cdot \left[\sum_{t=1}^{T} unspCFVC_{t,-} \cdot (1+r)^{T-t}\right] \\ +p_0 &\cdot \left[\sum_{t=1}^{T} unspCFVC_{t,0} \cdot (1+r)^{T-t}\right] \\ +p_+ &\cdot \left[\sum_{t=1}^{T} unspCFVC_{t,+} \cdot (1+r)^{T-t}\right] \end{aligned} \tag{2.27}$$

The terminal value of the exit-specific cash flows $FV_{spCFVC,T}$, on the other hand, is based on the future enterprise value at time of exit. The cash flow to the investor is dependent on the investment sum if and only if the scenario is of best case type. More formally, $FV_{spCFVC,T}$ is calculated as follows [based on A. Achleitner and E. Nathusius, 2004, p. 174]:

$$FV_{spCFVC,T} = p_+ \cdot ES \cdot FV_{U,T} \tag{2.28}$$

The calculation of the enterprise share ES at exit time is conducted by substituting Equations (2.24), (2.26) and (2.28) into the following Formula (2.29). The present value of the enterprise is calculated by division of the investment sum I and the enterprise share ES at exit time (see Equation (2.30)) [based on A. Achleitner and E. Nathusius, 2004, p. 175].

$$ES = \frac{I \cdot (1+r)^T - FV_{unspCFVC,T}}{p_+ \cdot FV_{U,T}} \quad (2.29) \qquad PV = \frac{I}{ES} \quad (2.30)$$

Finally, calculating the amount and the price of new shares to be issued is conducted in analogy to the venture capital method (the reader is referred to Equations (2.22) and (2.23) for more details).

As discussed earlier, classical venture valuation techniques require an active history of business activities (such as revenue or profit) in order to calculate enterprise worth [A. Achleitner and E. Nathusius, 2004, p. 184]. Due to the fact that the present work solely addresses the early-stage enterprise type that is categorized in the seed- and start-up stages of the enterprise life cycle, corresponding enterprises of interest do not exist as long as they miss historic business activity datasets. Subsequently, classical venture valuation techniques and -methods become inapplicable. Therefore, the following passages discusses alternative rules of thumb that are independent of the enterprise's historic track record.

Rules of Thumb Especially applicable for the valuation of early-stage enterprises, *rules of thumb* belong to the category of situation-specific valuation methods and are commonly utilized by business angels [A. Achleitner and E. Nathusius, 2004, p. 145]. In contrast to the classical venture valuation techniques, rules of thumb are mainly deployed for reasons such as the abbreviation of decision-making processes in the course of contract negotiations of investments or the inapplicability of classical venture valuation techniques due to the early-stage enterprise's non-existent historic track record. However, the negligence of valuation constraints (such as historic track records) lead to a high variation in valuation outcomes due to high probability of occurrence of delusive effects. [A. Achleitner and E. Nathusius, 2004, pp. 183–184] The following passages visualize rules of thumb that are commonly utilized by business angels in the course of venture valuation processes of early-stage enterprises.

The Scorecard Method is a non-scientific valuation method that forecasts a pre-revenue valuation of the target enterprise on the basis of the average valuation of already funded enterprises of the same domain/region and the comparison of the valuation subject to other similar enterprises (peer group), calculating a relative metric based on certain *weighted factors*. The method was founded by *Bill Payne* and is therefore also commonly referred to as *Bill Payne method*. Naturally, the scorecard method highly depends on the average pre-money valuations of certain industry sectors, specific markets or domains of interest, due to the fact that this constant has a significant impact on the pre-revenue valuation. For instance, ARI [2017] and AngelList [2017] provide accurate and publicly available data on average valuations on the basis of a modifiable filter. Table 2.5 depicts an excerpt of average pre-revenue enterprise valuations on the basis of several filters.

Table 2.5: Excerpt of average pre-revenue enterprise valuations according to certain filters, based on AngelList [2017]

Filter	Criterion	Avg. pre-revenue valuation
Country	Austria	\$4.2m
Location	Silicon Valley	\$5.1m
City	London	\$3.2m
Industry sector	Big Data	\$4.6m
	Cloud computing	\$4.6m
	Virtual currency	\$4.4m
Incubator	Harvard Innovation Labs	\$5.2m
	Mozilla WebFWD	\$3.3m
Accelerator	Microsoft pb TechStars	\$4.6m
	MIT Global Founders' Skills	\$5.5m
University	Harvard	\$4.8m
	Stanford	\$5.0m
	Massachusetts Institute of Technology (MIT)	\$4.8m

More formally, the scorecard method's process of calculating the pre-revenue valuation V_{TE} of the target enterprise (subject of valuation) is conducted as follows [based on Payne, 2006, pp. 73–79; Payne, 2011a, p. 4]:

$$V_{TE} = V_{avg} \cdot \sum_{i=1}^{|F|} f_{i,max} \cdot f_{i,TE} \tag{2.31}$$

where V_{avg} is defined as the average enterprise pre-revenue valuation based on a certain filter (such as industry sector or location), F is specified as the set of quantifiable enterprise factors, $f_{i,max}$ states the default importance of a factor $f \in F$ and $f_{i,TE}$ defines the valuation of the comparison between the target enterprise and the peer group based on the factor f. Furthermore, the set of factors F and each corresponding importance $f_{i,max}$ are predefined by the scorecard method and stated as follows:

(i) 30% Strength of the management team

(ii) 25% Size of the opportunity

(iii) 15% Product/Technology

(iv) 10% Competitive environment

(v) 10% Marketing/Sales/Partners

(vi) 5% Need for additional investment

(vii) 5% Other

In order to enable the investor to easily compare the target- and peer group enterprises on the basis of the mentioned factors, the scorecard method provides a set of *decision-rules*, having the aim of quantifying certain qualitative criteria stated by the factors. For a detailed description of the scorecard's valuation factors, the reader is referred to Table 2.6, whereas the relative impact of a certain factor may lie within the range of $---$ and $+++$, that is, ranging from a considerably negative- to a considerably positive impact respectively.

In summary, the scorecard method is not regarded a scientific venture valuation method. However, Payne [2011a, p. 5] argues that the scorecard method gives investors the opportunity to compare enterprises and assists in deciding whether the valuation shall reside at the low- or high end of a certain range. As of recently, the scorecard method has reached a considerably high popularity level especially among business angels [Payne, 2011a, p. 1].

Table 2.6: Scorecard method – Valuation factors and their impact, based on Payne [2011a, pp. 6–7]

Factor	Property	Impact	Impact description
Strenght of the management team	Experience	$+$	Considerably high amount of business experience (in years)
		$++$	Industry sector experience
		$+++$	Experience as CEO
		$++$	Experience as COO, CFO, CTO
		$+$	Experience as product manager
		$-$	Sales/Technology experience
		$---$	No business experience
	CEO replaceable?	$+++$	Willing
		0	Neutral
		$---$	Unwilling
	Founder trainable?	$+++$	Yes
		$---$	No

To be continued…

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Factor	Property	Impact	Impact description
	Completeness of management team	$+++$	Complete and competent team
		$+$	Team selected but inoperative
		0	One competent manager
		$-$	Only the entrepreneur
Size of the opportunity	Target market size	$++$	> $100m
		$+$	$100m
		$--$	< $50m
	Revenue potential in five years	$++$	$20m–$50m
		$-$	> $100m (requires attitional funding)
		$--$	< $20m
Product/Technology	Product state	$+++$	Orders of customers available
		$++$	Considerably good feedback of potential customers
		0	Product definition well established, prototype available
		$---$	No product definition and prototype
	Product convincingness	$+++$	Highly convincing
		$++$	Convincing
		$---$	Not convincing
	Product duplicability by competition	$+++$	Patent protection
		$++$	Trade secret protection and product uniqueness
		$-$	Replication difficult
		$---$	No patents/trade secrets, duplication considerably easy
Competitive environment	Strength of competitors	$++$	Fractured, small players

To be continued…

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Factor	Property	Impact	Impact description
		$-$	Dominated, several players
		$--$	Dominated, single big player
	Strength of competitive products	$+++$	Weak competitive products
		$--$	Successful competitive products
Marketing/Sales/Partners		$+++$	Trial orders, secure sales channels
		$++$	Key partnership negotiated
		$++$	Key beta testers engaged
		$--$	No partners
		$---$	No discussion about sales channels
Additional funding		$+++$	Not needed
		0	Additional BA funding needed
		$--$	Additional venture capital needed
Other[12]		$++$	Positive factors
		$--$	Negative factors

The Berkus Method basically tries to valuate the corresponding progressing elements of the entrepreneur (team) that actively reduce the risk of possible future success [Berkus, 2016; Amis and Stevenson, 2001]. Subsequently, a precondition to the berkus method is stated in the fact that an early-stage enterprise will reach a certain level of revenue —for instance $20m according to [Berkus, 2016]—after five years since enterprise formation. More formally, the berkus method assigns valuations up to the amount of $0.5m to four elements of risk each. The basic valuation value and the corresponding risks are stated as follows [Berkus, 2016]:

(i)	$0.5m	Sound idea	(basic value)
(ii)	$0.5m	Prototype	(technology risk)
(iii)	$0.5m	Quality management team	(execution risk)
(iv)	$0.5m	Strategic relationships	(market risk)
(v)	$0.5m	Product rollout / Sales	(production risk)

[12] Additional other factors may be subjectively defined by the needs of the investor such as but not limited to customer feedback).

The overall valuation of the target enterprise V_{TE} is calculated by the summation of each risk factor valuation [based on Berkus, 2016]:

$$V_{TE} = \sum_{i=1}^{|R|} r_i \tag{2.32}$$

where R is defined as the set of risks and r_i is specified as the valuation of one risk factor ($r \in R$). As a consequence, the maximum pre-revenue of an early-stage enterprise valuated by the berkus method is defined as \$2.0m or \$2.5m as post roll-out value respectively.

The Risk Factor Summation Method utilizes —as opposed to the scorecard- and berkus methods—a considerably broader set of risk factors in order to calculate an overall pre-revenue valuation of an early-stage enterprise. Furthermore, the adjustment of an average valuation due to certain filters yields a more dynamic and realistic valuation process, the risk factor summation method is based on. According to Payne [2011b], the utilization of the risk factor summation method is beneficial, for it considers important exogenous economic factors. However, this method shall only be utilized in addition to other valuation methods due to its generalizing assumptions [Payne, 2011b].

More formally, the risk factor summation method calculates the valuation of a target enterprise V_{TE} as follows [based on Payne, 2011b]:

$$V_{TE} = V_{avg} + \sum_{i=1}^{|F|} f_i \cdot \$250.000 \tag{2.33}$$

where V_{avg} is defined as the average enterprise pre-revenue valuation based on a certain filter such as industry sector or location (see Table 2.5), F is specified as the set of quantifiable enterprise risk factors and f_i is stated as concretely instantiated risk factor f of F ($f \in F$). In particular, each risk factor f is chosen as follows [Payne, 2011b]:

(i) +2 Very positive, implying a considerably high enterprise growth

(ii) +1 Positive

(iii) 0 Neutral

(iv) -1 Negative

(v) -2 Very negative, implying a considerably low enterprise growth

Finally, the set of quantifiable enterprise risk factors F is comprised of the following list [Payne, 2011b]:

- Management
- Business stage
- Legislation risk
- Political risk
- Manufacturing risk
- Sales risk
- Marketing risk
- Funding risk
- Capital risk
- Competition risk
- Technology risk
- Litigation risk
- International risk
- Reputation risk
- Potential lucrative risk

The Method of Thirds is based on the fact that investments especially in the early stages of an enterprise result in its separation between the founders, management and investors. Typically, the founders hold two thirds of the enterprise's share due to the fact that management is conducted by them. Therefore, investors hold one third of the enterprise. The method of thirds is solely dependent on the enterprise's capital requirements and does not rely on any enterprise characteristics. Subsequently, the enterprise value is defined as the triple investment sum. [A. Achleitner and E. Nathusius, 2004, p. 185]

The Components Method calculates the enterprise value in the course of the valuation and summation of an enterprise's value components (such as the worth of the business idea, founder team, quality of an existing prototype et cetera). The corresponding value components are chosen by the investor who therefore needs a considerably large amount of industry- and investment-specific experience and domain knowledge. Due to its clear assignment of the value components, the components method is transparent and comprehensible in terms of its procedure. [A. Achleitner and E. Nathusius, 2004, p. 185]

The Price Ranges Method aims at filtering of non-growth-oriented firms. According to the literature, many business angels only invest in enterprises whose proclaimed enterprise value lies between a certain range (such as 1m and 3m Euro). The reason given for this position is that a low valuation conducted by the founders imposes a considerably high probability that the corresponding enterprise may not be growth-oriented. Subsequently, higher valuations conducted by business angles will lead to even less probability in reaching a certain target return. Naturally, the price ranges method does not rely on enterprise characteristics and therefore, A. Achleitner and E. Nathusius [2004, p. 186] highly recommend utilizing this method only in the course of a separate venture valuation analysis. [A. Achleitner and E. Nathusius, 2004, p. 186]

2.1.3 Evaluation of Investment Decision-making Criteria & Venture Valuation Methods

The purpose of the present subsection lies in the literature review concerning the evaluation of investment decision-making criteria and venture valuation methods. Despite the fact that both mentioned domains are evaluated utilizing the same scientific instrument, their fields of research are considerably different to each other. As a consequence, the literature review is based on different types of literature, that is, whereas venture valuation methods or techniques are commonly covered by scientific textbooks, investment decision-making criteria is predominantly stated in scientific articles and -studies. However, one major aspect both domains have in common, lies in the fact that the corresponding literature needs to cover the context of early-stage enterprises.

Evaluation of Investment Decision-making Criteria

The present topic evaluates characteristics of investors' investment decision-making criteria on the basis of relevant scientific articles.

A recent paper by Miloud, Aspelund, and Cabrol [2012] suggests that the most important criteria affecting investment decision-making of investors are stated as the *industry structure*, *business networking effects* and the *management team* of an early-stage enterprise. As for the industry structure, the authors showed that there exists a positive correlation between industry growth and the corresponding valuation [Miloud, Aspelund, and Cabrol, 2012, pp. 16–18]. Furthermore, the authors suggest that an early-stage enterprise's network—that is, the number of partners—also positively correlates to the corresponding venture valuation [Miloud, Aspelund, and Cabrol, 2012, pp. 18–19]. Nevertheless, as proposed by Alexy et al. [2012], these assumptions also apply to venture capitalists, that is, by leveraging their social networks, venture capitalists' willingness to invest in certain early-stage enterprises increases, positively affecting the valuation of these very enterprises. Finally, Miloud, Aspelund, and Cabrol [2012, p. 18] showed that there is a positive correlation between the quality of the entrepreneurial team and the corresponding valuation. However, the question arises, whether certain aspects of the entrepreneurial team's quality may be distinguished even further?

The literature on investment decision-making shows that many articles were issued analysing- and ranking valuation criteria of investors (in particular, venture capitalists) in terms of the management team of early-stage enterprises [Gruber et al., 2017, pp. 656–657]. In particular, the results obtained by Gruber et al. [2017, p. 661] suggest the following ranked aspects for valuating management teams in the context of a highly probable success rate of the corresponding early-stage enterprise:

(i) Industry sector experience

(ii) Educational programme

(iii) Level of education

(iv) Degree of the common bond between the management team

(v) Experience in personnel responsibility

However, Gruber et al. [2017, p. 661] have arrived at the conclusion that the deviation of weights among these criteria indicate the fact that there is no consensus among the venture capital sector on general success factors of management teams. Therefore, these findings hold—to a certain degree—factors of uncertainty due to subjectivity of valuation processes depending on certain aspects (such as valuators themselves).

Evaluation of Venture Valuation Methods

While highly accepted by investors such as venture capitalists, situation-unspecific total valuation methods (such as the DCF method) and market-oriented techniques miss practicability and may even be rated as inapplicable due to the fact that especially early-stage enterprises commonly do not generate revenue or profit while lasting in the seed phase [A. Achleitner and E. Nathusius, 2004, pp. 184, 192–193]. As a consequence, the present work considers these valuation method categories as not suitable for the valuation of early-stage enterprises.

Although being regarded a guidance level rather than a valuation method, situation-specific total valuation methods are future-oriented and may be easily conducted [A. Achleitner and E. Nathusius, 2004, p. 193]. However, even these methods may be considered infeasible. Especially in early-stage enterprise investment the importance of practicable, quickly calculable valuations of enterprises rises considerably. Additionally, one characteristic of early-stage enterprises can be seen in the non-existence of historic business activities, resulting in the fact that valuation methods based on this assumption may not be applicable. A solution to this problem may be seen in the utilization of the *rules of thumb* venture valuation category. A. Achleitner and E. Nathusius [2004, p. 184] discuss that these methods allow for a quick calculation of guidance levels even in the case of non-existent historic business activities [A. Achleitner and E. Nathusius, 2004, p. 184]. Therefore, the present work considers the more sophisticated rules of thumb (such as the scorecard- or berkus methods) that base the valuation on the current market situations, as beneficial for the utilization in the valuation of early-stage enterprises. However, it shall be noted that the calculation of a future value involves a considerably high uncertainty, especially for early-stage enterprises of the seed phase. [A. Achleitner and E. Nathusius, 2004, p. 184]

2.2 Methodology for Eliciting Requirements

In the the course of the *methodology*, the reader is informed about the approach and -instruments utilized by the present work in order to gain knowledge to answer the research questions. The remainder of this section is organized as follows: Subsection 2.2.1 outlines the problem definition including the associated research questions, whereas subsections 2.2.2 to 2.2.4 describe the designs of the *qualitative expert interview*, *quantitative questionnaire* and *historical data analysis* respectively.

2.2.1 Problem Definition & Research Questions

Predominantly, funding of ventures is addressed by investors such as *Business Angels* or *Venture Capital Funds*, who provide capital particularly needed in the early stages of the company formation and beyond. However, as a result of the considerably large amount of enterprises entering the European market [OECD, 2012; Eurostat, 2016b; WKO, 2016], potential investors face the problem of *information overload*. Due to its nature, information overload in the domain of venture valuation leads to the inapplicability of traditional *investment decision-making* criteria and -venture valuation methods. Therefore, the need for information filtering techniques based on computational *recommendation systems* emerges.

The main objective of the present specialization topic lies in the research of investors' investment decision-making criteria and utilized venture valuation methods. In particular, the following research questions will be answered:

(i) How can investment decision-making requirements and behaviours of investors be quantified for being used in a recommender system?

  (a) Which investment decision-making criteria are crucial to investors?

  (b) Which data needs to be provided by early-stage enterprises in order to be of interest to investors?

(ii) Which venture valuation methods best model the characteristics of early-stage enterprises?

(iii) How do the identified investment decision-making characteristics and venture valuation methods affect the model of a recommender system in the domain of early-stage enterprises?

In order to scientifically answer the mentioned questions, the methodological approach basically consists of three steps:

(i) Qualitative expert interview, needed to gain general insights in the domain of early-stage enterprise investment.

(ii) Quantitative questionnaire, needed for quantizing criteria and characteristics of the early-stage enterprise investment domain gained from the qualitative expert interview.

(iii) Based on the analysis of a dataset containing historical investment deals, decision rules are elaborated.

The knowledge gathered by the proposed methodological approach is utilized to answer the research questions and, subsequently, taken as direct input to the model building phase of the recommender system (the reader is referred to chapter 3 for a detailed elaboration on the recommender system).

2.2.2 Design of the Qualitative Expert Interview

The purpose of the *qualitative expert interview* lies in the collection of expert knowledge on investment decision-making criteria and venture valuation methods utilized by investors in the domain of early-stage enterprise investment. While the scientific design is mainly based on literature review, the results of the expert interviews build one major input factor to the quantitative questionnaire. Therefore, the following passages describe the main characteristics of the qualitative expert interview.

The scientific instrument utilized for conducting the process of knowledge collection is stated as the *strongly structured interview.* Atteslander [2006, pp. 123–125] describes the strongly structured interview as scientific instrument utilized to quantitatively gather/measure data. In contrast to other types of interview structures, the strongly structured interview needs to be based on a pre-built questionnaire and requires a well trained interviewer in order to guarantee correct execution. Therefore, the questionnaire contains 39 questions (open-, closed-, ordinal/categorical-, dichotomous typed) that are based on the literature review and are basically divided into the following categories:

(i) Characteristics of Investors

(ii) Venture Valuation

(iii) Characteristics of early-stage enterprises

(iv) Recommender System (Platform)

The reader is referred to Table A.1 in appendix A for a complete listing of the chosen questions. Although strongly structured interviews are commonly utilized as scientific instrument of gathering quantitatively comparable data, the present work utilizes this very structure of interviews in order to collect considerably dense- but precise knowledge. However, at this stage, there is no requirement on quantitative comparability within participants (the reader is referred to subsection 2.2.3 for detailed information on the follow-up quantitative questionnaire).

The type of the interview is stated as mix between *expert-* and *intensive interview.* The literature on methods of empirical social studies defines expert interviews as scientific instrument for gathering knowledge in the field of interest by the consultation of experts [Atteslander, 2006, p. 131]. However, the most important aspect in this regard is stated as the definition of target participants (experts). Compared to the constraints of the expert interview, the intensive interview type only differs in terms of duration and intensity. As for the present work, the interview type *expert interview* with an interview length of approximately 90 to 120 minutes is selected.

Due to the length- and type of the interviews, it is stated that the interviewer utilizes a *weakened form* of the *neutral interview*. According to Atteslander [2006, p. 128], the weakened form of the neutral interview requires the interviewer to show confidence about the personal seriousness towards the interview. On the other hand, the interviewer shall not appear to be too formal. Thus, the interviewed person needs to perceive the interviewer as being interested in the topic of discussion. However, the most important aspect the interviewer needs to comply with is *neutrality* itself, that is, the interviewer must keep the personal opinion towards the topic of discussion out of the interview and needs to try not to bias the interviewee in any regard. Sticking to this plan will keep the interviewee motivated over long interview sessions while guaranteeing unbiased results.

The participants for the interviews shall be experts in the field of early-stage enterprise investment. This criterion about the characteristics of experts especially applies to investors such as business angels, but also includes experts in the field such as researchers working for incubators, accelerators, aid money agencies specialised in the field of early-stage enterprises or universities.

The process of conducting the expert interviews conforms to the following setting and procedure:

(i) Setting:
   (a) Participant (Interviewee)
   (b) Interviewer
   (c) Secretary
   (d) Neutral meeting location: Office / Café

(ii) Procedure:
   (a) The interviewer describes the interview (characteristics) and instructs the participant.
   (b) The interviewer starts the conversation and asks questions based on the preliminary questionnaire.
   (c) The secretary keeps track of the journal and maintains the audio recording.

In order to evaluate whether the chosen scientific design may deliver the expected results, a pretest was conducted. It has been found that some of the prepared questions were leading to false assumptions on the crucial point of interest and were therefore remodelled. Additionally, the original questionnaire contained too many questions, leading to an average interview length of approximately 180 minutes. Thus, the final questionnaire was designed to contain less questions in order to reach a maximum interview length of 120 minutes.

Finally, the results of the qualitative expert interviews are analysed and evaluated (the reader is referred to subsection 2.3.1 for a detailed evaluation of the gathered knowledge). The evaluation itself—while based on four question categories—considers the results with the highest level of agreement among participants aligned with the literature and participants' *innovative ideas*, which might especially be relevant in the context of a recommender system platform in the area of early-stage enterprise investment. Based on the evaluation, questions for the quantitative questionnaire are designed in a more precise and quantifiable way in order to gather the degree of agreement on the qualitatively researched knowledge. Figure 2.5 shows the transitioning process from the qualitative questionnaire's results to the quantitative questionnaire's questions in more detail.

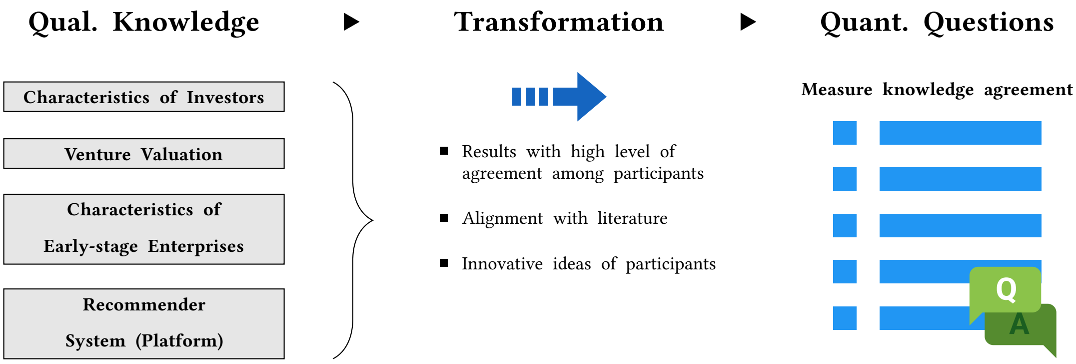

Figure 2.5: Transition process from the qualitative questionnaire's results to the quantitative questionnaire's questions.

2.2.3 Design of the Quantitative Questionnaire

The *quantitative questionnaire* is based on the results of the literature review as well as the qualitative expert interviews. Its main goal is stated as the collection of quantitatively comparable data about certain aspects-, criteria- and characteristics in the domain early-stage enterprise investment. The gathered data is regarded the basis for statistical analyses, -tests and -evaluations. Subsequently, the results of the quantitative questionnaire directly influence the (data)model of the recommender system. The following passages describe the main characteristics, questions and statistical tests of the quantitative questionnaire in great detail.

The scientific instrument utilized for conducting the process of gathering quantitatively comparable data is stated as the written form of the *quantitative questionnaire*. In order to deliver comparable responds between participants, it is important to choose the correct answer set and, subsequently, select the appropriate statistical data type according to the corresponding type of question. The following passage further describes the elaborated questions.

Questions

Based on the evaluation of the qualitative expert interviews' results (the reader is referred to subsection 2.3.1 for a detailed analysis), seven questions were constructed for being utilized in the course of the quantitative questionnaire (Table 2.7 depicts these questions, translated from German).

Table 2.7: Questions of the quantitative questionnaire

Idx	Type	Question
Q1	Likert (Ordinal, 1–5)	Based on which criteria do you decide upon, whether an investment in an early-stage enterprise shall be conducted?
Q2	Likert (Ordinal, 1–5)	Which characteristics does an early-stage enterprise need in order for you to consider investing?
Q3	Dichotomous/Binary (Yes/No)	Are you able to predict the success/failure of an early-stage enterprise in the (pre-)seed stage?
Q4	Likert (Ordinal, 1–5)	Which characteristics of early-stage enterprises are important for venture valuations?
Q5	Likert (Categorical; 1–4)	Due to the fact that early-stage enterprises of the (pre-) seed stage lack a historic track record of business activities, a valuation is hardly feasible or completely impossible. Therefore, especially business angels utilize self-defined best practices and rules of thumb as valuation methods, which are already discussed by scientific literature. Which of the following valuation methods do you use?
Q6	Likert (Ordinal, 1–5)	Which functionality should a platform for recommending early-stage enterprises to investors provide in order to offer additional value to you?
Q7	Likert (Ordinal, 1–5)	According to which criteria shall recommendations be generated?

Questions Q1, Q2 and Q4 to Q7 are of *Likert* type, that is, these questions are constructed of an overall question that contains a certain amount of sub-questions sharing the same domain and answer set [Atteslander, 2006, p. 222]. This type of answer set is commonly based on an ordinal scale ranging between an interval of two rational integers such as $1 \ldots 5$ or $1 \ldots 7$. Each answer type of a Likert question is attached to one rational integer within the corresponding interval. Likert questions are commonly utilized to measure the degree of participants' (dis)agreement among certain statements. Therefore, the semantics of the correlation between the rational integers of the scale and the attached answer types comply to the following rule: The lower end states that the participant disagrees, while the upper end means full agreement. The present work's default answer set utilized in combination with Likert scales is depicted in the following listing:

1 … Unimportant
2 … Rather unimportant
3 … Neutral
4 … Rather important
5 … Important

The following passages illustrate the quantitative questionnaire's questions in great detail.

Question 1: Based on which criteria do you decide upon, whether an investment in an early-stage enterprise shall be conducted? The main objective of this question is to gain insights on the importance of certain criteria the investor bases investment decisions on. Therefore, this question's type is constructed of several sub-questions that share the same rating scale, that is, a Likert-type question and sub-questions based on an ordinal scale. Due to illustration purposes, each Likert sub-question is assigned an index that is utilized throughout the present work instead of the corresponding sub-question's description. The reader is referred to Table 2.8 for a representation of the index/sub-question mappings.

Table 2.8: Question 1 – Likert index/sub-question mappings

SQ	Sub-question
SQ1	Recommendations (e.g. by investors)
SQ2	Historic investment decisions
SQ3	Relationship to entrepreneur(s)
SQ4	Industry sector
SQ5	Experience of entrepreneur(s)
SQ6	Return on investment vs. risk
SQ7	Market research
SQ8	Valuations of ventures
SQ9	Geographical business location
SQ10	Market of the early-stage enterprise (geographical)

Question 2: Which characteristics does an early-stage enterprise need in order for you to consider investing? Gaining insights on the importance of certain early-stage enterprises' characteristics that need to be fulfilled in order to make an investor consider investing is stated

as the main objective of question Q2. Therefore, this question's type is constructed of several sub-questions that share the same rating scale, that is, a Likert-type question and sub-questions based on an ordinal scale utilizing the following answer set:

1 ... Unimportant
2 ... Rather unimportant
3 ... Neutral
4 ... Rather important
5 ... Essential

Due to illustration purposes, each Likert sub-question is assigned an index that is utilized throughout the present work instead of the corresponding sub-question's description. The reader is referred to Table 2.9 for a representation of the index/sub-question mappings.

Table 2.9: Question 2 – Likert index/sub-question mappings

SQ	Sub-question
SQ1	Team: Former experience as CEO
SQ2	Team: Former experience as COO, CFO, CTO
SQ3	Team: Existent knowledge to implement the product idea
SQ4	Team: Founder team consists of min. 2 persons
SQ5	Team: Founder is willing to step back (if needed)
SQ6	Team: Own funds at time of foundation
SQ7	Product idea elaborated (prototype implemented)
SQ8	Product idea elaborated (prototype not implemented)
SQ9	Product idea available and rudimentarily elaborated
SQ10	Product idea protected by patents
SQ11	Industry sector is not saturated. Market entry of the product idea possible
SQ12	Market analysis / Industry sector analysis / venture valuation available
SQ13	Plausibility of the enterprise formation

Question 3: Are you able to predict the success/failure of an early-stage enterprise in the (pre-)seed stage? In the course of the present work, experience of investors is considered a highly important criterion for the model building phase of the recommender system. As a consequence, the main objective of this question is to gain insights on the fact whether a participant feels capable of predicting the success or failure of an early-stage enterprise while still lasting in the (pre-)seed stage. The intention behind this question is its utilization as independent variable, which enables the splitting of the data. Subsequently, the emerging dataset allows for statistical tests, that is, measuring the deviation of the dependent variable between two groups of participants: Experienced- and inexperienced investors. Therefore, this question's type is stated as *dichotomous (binary)*, that is, an answer set of $\{Yes, No\}$.

Question 4: Which characteristics of early-stage enterprises are important for venture valuations? The main objective of this question is to gain insights on the importance of certain early-stage enterprise characteristics needed in the course of a valuation. Therefore, this question's type is constructed of several sub-questions that share the same rating scale, that is, a Likert-type question and sub-questions based on an ordinal scale. Due to illustration purposes, each Likert sub-question is assigned an index that is utilized throughout the present work instead of the corresponding sub-question's description. The reader is referred to Table 2.10 for a representation of the index/sub-question mappings.

Table 2.10: Question 4 – Likert index/sub-question mappings

SQ	Sub-question
SQ1	Opportunity (market situation, revenue in 5 years)
SQ2	Maturity level of the product idea
SQ3	Customer acceptance of the product idea
SQ4	Equity capital / financial assets of the founders
SQ5	Industry structure (market entry barriers, market growth)
SQ6	Competition
SQ7	Number of founders > 1
SQ8	Experience of the founder team
SQ9	Founders already have experience in founding- and running early-stage enterprises

Question 5: Due to the fact that early-stage enterprises of the (pre-) seed stage lack a historic track record of business activities, a valuation is hardly feasible or completely impossible. Therefore, especially business angels utilize self-defined best practices and rules of thumb as valuation methods, which are already discussed by scientific literature. Which of the following valuation methods do you use? The main objective of this question is to gain insights on the fact whether investors *utilize* or at least *know* certain venture valuation methods. As of the outcome of the investment decision-making & venture valuation specialization topic, this question is considered the most important among all questions. Due to its structure, this question's type is defined as several sub-questions that share the same rating scale, that is, a Likert-type question and sub-questions with an answer set that is divided into four categories (nominal/categorical scale):

1 ... Do not know (implicates non-usage)

2 ... Know (implicates non-usage)

3 ... Do not use (implicates knowledge)

4 ... Use (implicates knowledge)

Due to illustration purposes, each sub-question is assigned an index that is utilized throughout the present work instead of the corresponding sub-question's description. The reader is referred to Table 2.11 for a representation of the index/sub-question mappings.

Table 2.11: Question 5 – Likert index/sub-question mappings

SQ	Sub-question
SQ1	Scorecard Method
SQ2	Berkus Method
SQ3	Risk Factor Summation Method
SQ4	Venture Capital Method
SQ5	First Chicago Method
SQ6	Real Options Approach
SQ7	Experience

Question 6: Which functionality should a platform for recommending early-stage enterprises to investors provide in order to offer additional value to you? Gaining insights on the importance of certain characteristics of a potential recommender system for recommending early-stage enterprises to investors is stated as the main focus of question Q6. Therefore, this question's type is constructed of several sub-questions that share the same rating scale, that is, a Likert-type question and sub-questions based on an ordinal scale. Due to illustration purposes, each Likert sub-question is assigned an index that is utilized throughout the present work instead of the corresponding sub-question's description. The reader is referred to Table 2.12 for a representation of the index/sub-question mappings.

Table 2.12: Question 6 – Likert index/sub-question mappings

SQ	Sub-question
SQ1	Visualization of detailed data concerning early-stage enterprises (private area)
SQ2	Public profile of early-stage enterprises (for measuring customer acceptance)
SQ3	Investment profile for investors (favourite industry sectors, product interests, investment amount, ...)
SQ4	Straightforward setup assistant for configuring the investment profile
SQ5	Filtering early-stage enterprises according to personal preferences
SQ6	Highlighting of popular early-stage enterprises (high public/investor interest)
SQ7	Visualization of pre-money valuations of early-stage enterprises
SQ8	Visualization of investment amount vs. risk
SQ9	Visualization of the founder team's experience
SQ10	Smartphone application
SQ11	E-Mail / Push notification at availability of new interesting early-stage enterprises
SQ12	Anonymity to visitors of the platform (visitors are neither investors, nor innovators)

Question 7: According to which criteria shall recommendations be generated? The main objective of this question is to gain insights on the importance of certain criteria venture recommendations shall be based upon. Therefore, this question's type is constructed of several sub-questions that share the same rating scale, that is, a Likert-type question and sub-questions based on an ordinal scale. Due to illustration purposes, each Likert sub-question is assigned an index that is utilized throughout the present work instead of the corresponding sub-question's description. The reader is referred to Table 2.13 for a representation of the index/sub-question mappings.

Table 2.13: Question 7 – Likert index/sub-question mappings

SQ	Sub-question
SQ1	Include early-stage enterprise recommendations that do not match your investor's profile
SQ2	Recommendations based on your former investment decisions
SQ3	Recommendations based on the investments or interests of other (certain) investors
SQ4	Recommendations based on an investor's profile
SQ5	Recommendations based on balancing your investment portfolio (risk vs. revenue)
SQ6	Recommendations based on the pre-money valuation of early-stage enterprises

Statistical Tests

The following passages describe the utilized statistical tests in great detail.

Prior to statistical tests whose goal lie in answering certain hypotheses, a test for reliability and normality is applied to the collected dataset. Reliability measures the utility of the scientific instrument, that is, highly reliable instruments deliver the same results for repeated measurements of the same input factors. More formally, reliability measures a scientific instrument's degree of variance for repeated measurements. Typical methods for measuring reliability of a scientific instrument may be seen in a retest of the corresponding measurement or the *split-half method*[13]. [Atteslander, 2006, p. 215] In the case of Likert questions, reliability is interpreted as the *internal consistency* among all sub-questions. Cronbach defines internal consistency as follows:

> “ …During the last ten years, various writers directed attention to a property they refer to as homogeneity, scalability, internal consistency, or the like. The concept has not been sharply defined, save in the formulas used to evaluate it. The general notion is clear: In a homogeneous test, the items measure the same things.
>
> If a test has substantial internal consistency, it is psychologically interpretable.

[13] Split-half method: A statistical data scale is split into two parts under the constraint that the contained elements (items) are equally assigned to the corresponding split datasets. The utility of the scientific instrument is calculated by correlation of each split scale's measurements. [Atteslander, 2006, p. 215]

> Two tests, composed of different items of this type, will ordinarily give essentially the same report. If, on the other hand, a test is composed of groups of items, each measuring a different factor, it is uncertain which factor to invoke to explain the meaning of a single score. For a test to be interpretable, however, it is not essential that all items be factorially similar. What is required is that a large proportion of the test variance be attributable to the principal factor running through the test. ...
>
> *Cronbach [1951, p. 320]* ”

Furthermore, internal consistency is commonly measured utilizing Cronbach's *alpha*, who describes this statistic as follows:

> “ ... α estimates the proportion of the test variance due to all common factors among the items. That is, it reports how much the test score depends upon general and group, rather than item specific, factors. ...
>
> *Cronbach [1951, p. 320]* ”

α itself is a real number ≤ 1 although negative values may only be interpreted as the application of an *incorrect measurement model* or *considerably bad scores* [Ritter, 2010, p. 8]. In fact, α of interval $0 \ldots 1$ complies to the following assumptions [Ritter, 2010, pp. 9–11]:

- $\alpha = 1 \ldots$ Perfect internal consistency between items' scores, that is, items correlate perfectly.
- $\alpha = 0 \ldots$ No internal consistency between items' scores, that is, items are perfectly uncorrelated.

According to Nunnally [1967, p. 226], a satisfactory α value depends on the field of application the measure is being utilized for. Therefore, for early stages of research, an α value of $0.50 \ldots 0.60$ is sufficient. Basic research, on the other hand, requires a value of 0.80. Nunnally [1967, p. 226] further states that in research domains where important decisions are being made (such as in clinical domains), an α of $0.90 \ldots 0.95$ shall be considered a minimally tolerable or desirable standard respectively. However, Streiner [2003, p. 103] argues that Nunnally raised the minimal α value for early stages of research to 0.70 in the second edition of his book *Psychometric theory*[14]. Furthermore, Streiner claims that considerably high α values, that is, $\alpha > 0.90$, may indicate redundancy among items. As a consequence, the present work complies to the common rule of thumb and considers the following interval of α values as being acceptable: $0.70 \leq \alpha \leq 0.90$.

The second preliminary statistical test is stated as *test for normality*, that is, testing whether the responds of each Likert type sub-question are normally distributed. The reason for this test

[14] Nunnally, 1978.

lies in the fact that the corresponding parametric statistical tests require a normally distributed dataset. If this requirement is not fulfilled, these tests can not be applied. Due to its high statistical power especially for small population/sample sizes [Seier, 2002; Razali and Wah, 2011, pp. 27–32], the present work utilizes the *Shapiro-Wilk* test of normality [Shapiro and Wilk, 1965].

In order to answer research questions about investment decision-making criteria and venture valuation methods, the definition of *significant results* needs to be conducted. The present work predefines, that the answer sets *4* and *5* of the Likert questions Q1, Q2, Q4, Q6 and Q7—that is, *Rather important* and *Important/Essential*—, are utilized for the indication of beneficial utility. In contrast to these ordinal scaled Likert questions, the beneficial utility of the categorical Likert question Q5 is stated as the most frequently utilized answer sets. Due to the fact that the author supposes that there is a possible difference in the distribution of answer sets among experienced- or inexperienced investors, it is stated that the opinion of experienced investors is weighted considerably higher than the ones of their inexperienced counterparts, subsequently biasing the decision about the beneficial utility of a certain Likert sub-question. As will be stated in the results of the qualitative expert interviews, the definition of an investor's experience is a non-trivial task, that is, trivial correlations between certain independent variables (such as invested- vs. raised money) and the dependent variable of *investment experience* is generally not feasible. Therefore, the present work predefines that experience of an investor is treated as *unknown* and *unmeasurable*, stated by the participants themselves and quantitatively measured by question Q3 as a dichotomous variable (binary; *Yes/No*). However, there are certain challenges in the determination of the appropriate statistical tests supporting the mentioned characteristics that need to be tested.

Since the perceived *semantic distances* between each rational integer within an ordinal (or even categorical) scale differ from their actual quantitative measurements [Atteslander, 2006, p. 216], care needs to be taken when defining statistical tests. As a consequence, the author assumes that most response sets of the Likert questions are not normally distributed. Subsequently, most *parametric statistics/tests* may not be applied to the collected datasets, because of the requirement of normally distributed data. Therefore, the corresponding *non-parametric statistics/tests*—that do not rely on certain assumptions on the data's probability distribution—are being utilized to answer certain hypotheses on the beneficial utility of Likert sub-questions. The correlation between a statistical test and the corresponding hypothesis grouped by each Likert type question of the quantitative questionnaire is listed in Table 2.14.

As for the measurement of beneficial utility among all Likert questions' sub-questions, the *Wilcoxon Signed Rank Test* is utilized. This non-parametric test basically measures whether the distribution of participants' responds is symmetric about a hypothesized location [Wilcoxon, 1945; ETH Zurich, 2017b]. In order to test whether there is a statistically significant difference between experienced- and inexperienced investors, two tests—depending on the Likert question's underlying scale (ordinal or categorical)—are chosen: *Wilcoxon Rank Sum Test* and *Fisher's Exact Test* [Wilcoxon, 1945; ETH Zurich, 2017b; Fisher, 1922; ETH Zurich, 2017a]. Whereas the former tests whether there is a location shift between the distributions of two populations (participants' responses grouped by the *experience* variable), Fisher's Exact Test utilizes *contingency tables* to classify objects—that is, participant groups and each answer type of the answer set—in different ways. Subsequently, statistical significance is examined by testing whether rows and columns of the contingency table are independent. Because of it's nature, Fisher's exact test is especially beneficial when utilized for categorically scaled data. Due to the fact that this test does not rely upon approximation—that is, ρ values are calculated exactly—its utilization is advantageous when applied to small population sizes (as is the case in the present work, see section B.5 in appendix B). The reader is referred to subsection 2.3.2 for a detailed visualization of the procedure for conducting the mentioned statistical tests.

Table 2.14: Statistical tests / Hypotheses of the quantitative questionnaire's Likert type questions

Question(s)	Statistical Test	Hypothesis/Research Question
Q1, Q2, Q4, Q6, Q7	Wilcoxon Signed Rank T.	Is there statistical significance about the fact that participants rated a certain sub-question either *Rather important* or *Important/Essential*?
	Wilcoxon Rank Sum T.	Is there statistical significance about the fact that experienced- and inexperienced investors have a different opinion on a certain sub-question
Q5	Wilcoxon Signed Rank T.	Is there statistical significance about the fact that participants did not rate a sub-question with a specific response from the answer set (therefore, the answer sets being not statistically significant are to ones of beneficial utility)?
	Fisher's Exact T.	Is there statistical significance about the fact that experienced- and inexperienced investors have a different opinion on a certain sub-question?

Characteristics and Procedure of the Quantitative Questionnaire

The participants of the quantitative questionnaire shall be experts in the field of early-stage enterprise investment. This criterion about the characteristics of experts especially applies to investors such as business angels, but also includes experts in the field such as researchers working for incubators, accelerators, aid money agencies specialised in the field of early-stage enterprises or universities.

The process of conducting the quantitative questionnaire conforms to the following procedure:

(i) An invitation to the online accessible questionnaire is sent to the corresponding participant via e-mail.

(ii) The participant reads the introduction and advise on the questionnaire.

(iii) The participant completes the online questionnaire.

(iv) The results are stored for later analysis and evaluation.

Finally, the results of the quantitative questionnaire are analysed and discussed (the reader is referred to subsection 2.3.2 for a detailed evaluation of the datasets). Additionally, appendix B depicts the original raw data, descriptive statistics, statistical tests and the process of analysis utilizing the statistics software *R*[15] in great detail.

2.2.4 Historical Data Analysis

The purpose of the present subsection lies in the quantitative analysis of a dataset holding records of investments, with the goal of deducting investment decision-making rules based on this very data. For instance, one rule might answer the question whether investors tend to invest in the same industry sector or rather switch sectors throughout their investment career. In particular, the dataset itself is a snapshot of the *Crunchbase*[16] online service that actively maintains a database of ventures and their surrounding business activities. The snapshot of the dataset is provided by [Zhao, Zhang, and Wang, 2015] and contains records of the time period of May 2014. The constructed set of rules will directly influence the model building phase of the recommender system. The reader is referred to subsection 2.3.3 for an elaboration of the results.

[15] The R Project for Statistical Computing: [R Foundation, 2017]
[16] Crunchbase: https://www.crunchbase.com/

2.3 Results of the Requirements Analysis

In the the course of the present chapter, the reader is informed about the analysis and evaluation of the results obtained by conducting the scientific processes specified in the methodology chapter. The remainder of this chapter is organized as follows: Each subsection covers the results of one of the three scientific instruments, that is, subsection 2.3.1 covers the results of the *qualitative expert interviews*, subsection 2.3.2 outlines the *quantitative questionnaire's* results and finally, 2.3.3 studies the results of the *historical data analysis*.

2.3.1 Qualitative Expert Interview Results

The qualitative expert interviews' main goal was to gain experts' knowledge in the area of early-stage enterprise investment. In particular, it is the literature review/evaluation and the outcome of the present subsection that build the basis for the quantitative questionnaire (the reader is referred to subsections 2.2.3 and 2.3.2 for further information), that is, research on the the design of the quantitative questionnaire including quantifiable questions. In the course of this subsection, details and challenges of the qualitative expert interviews are discussed, followed by the evaluation grouped by question category.

As for the execution of the qualitative expert interviews, the response rate of participants taking the questionnaire lasts at a considerably low percentage of ~21.4%, that is, 6 out of 28 persons. Reasons justifying this unsatisfactory response rate may be seen in the fact that a considerably large amount of the contacted investors did not participate because they have not had the times to do so. Of course, one of the findings gained from the conducted interviews was the general response that the interview length was too long, that is, an interview length of maximum 60 minutes instead of 90 to 120 minutes would have been preferred by most participants. This finding in combination with the considerably low response rate was an indication to make the quantitative questionnaire accessible at an online setting and achievable within a ten minute time frame.

Furthermore, finding participants who conform to the stated participant profile/type turned out to be a non-trivial endeavour. In fact, solely relying on e-mail- or telephone communication did not turn out to gain the anticipated results. As a consequence, networking and personal meetings needed to be utilized in order to increase the number of participants. Subsequently, a significant raise in the response rate was achieved. Due to the fact that the goal of the qualitative expert interviews was not to deliver comparable- and quantifiable knowledge between participants, the present work justifies that the amount of conducted interviews in terms of scientific justification is acceptable. However, future research may strive for an increased response rate.

Due to visualization purposes, the following *analysis* passage summarizes the results of the qualitative expert interviews grouped by question category/type. Subsequently, the general evaluation and the proposed implications for the quantitative questionnaire are discussed in the *evaluation* passage. For the purpose of consistency to the present work, question categories —including all questions—were translated from German. The reader is referred to Table A.1 in appendix A for a complete listing of the questions.

Analysis

In the course of this passage, the collected data among all expert interviews is analysed and summarized according to the general question categories.

Characteristics of Investors In the context of the enterprise life cycle, the participants generally preferred the seed-, start-up- and expansion stages for early-stage enterprise investments. However, these stages need to be rated inferior, that is, early-stage enterprises need to be categorized by certain achievements already made (such as a sophisticated definition of the product idea). In order to analyse an early-stage enterprise's intentions and characteristics, sufficient data needs to be provided.

Early-stage enterprises commonly introduce themselves to investors by showcasing a business plan and conducting a presentation of the business—which is also referred to as *pitch*. The most important aspects of the business plan is outlining the team, product idea, value proposition and needed resources (equity capital, knowledge et cetera). Personal opinions on the meaningfulness of the business plan are scattered among participants. Whereas some think that business plans are not important any more, others argue that the business plan is more trustworthy than pitching slides. Additionally, there was an advice about the fact that business plans are less important in the initial stage of an early-stage enterprise, but rather become more important in the later stages. Therefore, pitch slides or -videos (showcasing the team and the product idea) are considered most important in the beginning. However, all participants agreed on the fact that external advice in the form of market- and industry sector analyses need to be conducted in order the check an early-stage enterprise's potential for success or failure. These analyses play an important role in indicating whether an investment shall be conducted.

Another important characteristic investors base their investment decisions on, may be seen in the *team* of an early-stage enterprise. In particular, facts such as experience of the entrepreneurs, the whole team's chemistry or a minimum amount of two entrepreneurs—a backup plan in case of one entrepreneur's resignation—were mentioned by the participants. Furthermore, investments in an early-stage enterprise additionally depend on its industry sector, the geographical location of its market (such as the European Union), its corresponding market potential and its products' value propositions. Independently, investors constantly need to weigh risk vs. potential return on investment and therefore need to be aware of the fact that investments based on private equity capital may be lost in its entirety. Participants' opinions state that the more experienced an investor becomes, the more risk awareness rises. Subsequently, an investor's goal is the reduction of investment risk. This process is supported by an investor's experience gained from previous investment decisions. In particular, participants reported on the fact that at a certain level of experience, investors try to build *investment portfolios* containing multiple early-stage enterprises (20+ at best), with the purpose of reducing risk of total loss by distribution onto certain segments (early-stage enterprises).

However, one of the most important facts arising from the present question's group is stated as *trust relationships* between investors. Participants were in complete agreement on the fact that investors include other investors' opinions into certain aspects of their own investment decision-making criteria. This behaviour is based on a variety of possibilities such as consulting, collective investments among investors driven by a lead investor or the distribution of investment risk among investors by split of the investment sum. Furthermore, participants reported that most investors collaborate with each other or at least in certain *circles* or *inner circles.* However, despite the author's expectation, participants stated that *rivalry* among investors is no major concern.

Venture Valuation Interestingly, the one aspect participants found a consensus upon, is also seen as the most important aspect for forecasting the success of an early-stage enterprise: the early-stage enterprise's *(management) team.* According to the participants, the size of the founding members of an early-stage enterprise—also referred to as management team—shall at least be stated as two persons (backup strategy). Furthermore, the maturity level of the product (idea), preallocated customers, location, industry sector and competitiveness may be seen as additional important factors. However—analogously to the previous passage—an external view in the course of a market analysis shall still be conducted in order to conclude more objective- and realistic information on the early-stage enterprise in the context of the corresponding market.

As was expected in the course of literature review, the answers of participants support the opinion that classical venture valuation methods (such as fundamental-analytic techniques) can not be utilized for the valuation of early-stage enterprises, due to the unavailability of historic business activities. However, these methods might still be utilized in certain cases (combined with experience), because investors are also driven by emotion and the belief that there are literally *no better approaches available.* In regard to the latter statement, participants mentioned the importance of comparing an early-stage enterprise's characteristics to the ones of a set of already well established peer ventures. Nevertheless, participants' answers about early-stage enterprise specific venture valuation methods were—as expected—*not satisfying*. The reason for this rating can be seen in the fact that most of the discussed methods were not utilized by the participants and only a few of them were known, such as the venture capital method and the real options approach (despite the fact that most participants think the latter is not meaningful and hardly applicable at all, because of the impossibility of forecasting *all* probable future events). However, the method *experience* was —again—of highest priority.

Characteristics of Early-stage Enterprises As already mentioned in the previous passage, the (management) team, its minimum size (two persons) and additionally the internal chemistry between founders are considered the most important characteristics of early-stage enterprises, biasing investors' decisions towards an agreement on certain investments. Further important aspects include the innovation of the product (idea), size of the market, sales strategy, unique selling proposition (USP) and international orientation (global, not limited to the DACH[17] region). Additionally, participants stated that the founders shall be financially educated.

The minimum requirements for investors to decide upon investing in a certain early-stage enterprise were stated by the participants as the founders' incentive of investing own funds (if

[17]DACH: European region involving Germany, Austria and Switzerland (Confoederatio Helvetica)

possible), diversity among the management team (distribution of responsibilities) and plausible information in the business plan and pitching slides. On the other hand, investors will certainly not invest, if the entrepreneurs were to make false statements about their early-stage enterprises, the team is inflexible or there are possible legal issues.

Recommender System (Platform) The final category of questions addresses possible approaches and functions of the recommender system platform. In general, participants were rather sceptical about the whole idea of automatic recommendation of early-stage enterprises to investors. However, answers to the question about general requirements to such a system were rather concrete:

- Possibility to rate teams and, subsequently, rank early-stage enterprises depending on the responsible team.
- Calculation of metrics for valuation purposes.
- Analyses of markets.
- Analysis of the competitive landscape (other similar early-stage- and already established enterprises in the corresponding industry sector)
- Tracking of business activity (if applicable)
- Investor profiles (very important)

Furthermore, some participants generally defined the goal of the present recommendation system as the collection of dense data sets allowing the view of metrics, early-stage enterprises et cetera among certain market locations (such as the European Union, DACH, or the United States). Other important aspects also include the recommendation of early-stage enterprises from investor to investor and rather technical specifications such as the ease-of-use of the platform, push-notifications and short video slides introducing the corresponding early-stage enterprise to investors.

Another major aspect of the recommendation system can be seen in finding a match between investors and certain early-stage enterprises. According to the participants, this process may be modelled by defining matches based on an early-stage enterprise's industry sector, stage of the enterprise life cycle, needed capital or similarity to other early-stage enterprises. From the investor entity's perspective, one major decision criterion is seen in the amount of needed capital. However, the present recommendation system faces certain challenges as well.

Based on the participants' opinions, the most severe challenges the present recommendation platform is about to face, is seen in the process of collecting data on existing (early-stage) enterprises and market dynamics, insufficiency in data provided by investors themselves (such as for an investor's profile or certain search criteria) and the general modelling of experience.

Evaluation & Design of Quantitative Questions

Based on the previous passage, the following paragraphs evaluate the findings of the analysis and discuss possible outcomes and implications on the design of the quantitative questionnaire.

The analysis of participants' responds on the characteristics of investors shows that investors have a clear opinion on the fact whether an investment in an early-stage enterprise is lucrative or not. The most important aspects, to name a few, are stated as the team, industry sector, recommendations by other investors and valuations of early-stage enterprises. When compared to the literature (the reader is referred to section 2.1 for a detailed elaboration), early-stage enterprise characteristics important to the investor are highly similar to the *valuation factors* of the *scorecard-* and *berkus* valuation methods. Therefore, it is important for the quantitative questionnaire to include a question category about the very aspects an investor bases investment decisions upon. Subsequently, this question category is based on the valuation factors of the scorecard/berkus methods and additionally includes important aspects depicted in the previous analysis passage.

According to the analysis on the venture valuation topic, the most important aspects depicting the success of an early-stage enterprise is, again, seen in it's (management) team, product (idea) or industry sector. Furthermore, classical venture valuation methods are not applicable to early-stage enterprises due to non-existent historic business activities. Analogously to the previous paragraph, these findings highly correlate with the valuation factors of the scorecard/berkus valuation methods discussed in the literature. Due to the mentioned facts, questions about early-stage enterprise characteristics important for their valuation, and known/utilized early-stage enterprise specific valuation methods are of high interest and therefore included in the quantitative questionnaire.

Another important finding of the previous analysis may be seen in the characteristics of early-stage enterprises important to investors. As the participants stated, these aspects include characteristics such as the (management) team, innovation of the (product idea) or an early-stage enterprise's international orientation. Therefore, it is important for the quantitative questionnaire to include a question category about early-stage enterprise characteristics that bias investors' investment decision-making requirements.

Interestingly, the analysis phase further showed that participants had a considerably large amount of concrete requirements to a potential platform for recommending early-stage enterprises to investors. The most important idea is stated as an *investor profile* that enables the modelling of an investor's interest and personal decision rules utilized for matching early-stage enterprise characteristics. Therefore, questions of interest that shall be included in the quantitative questionnaire may be defined as requirements the recommendation system shall fulfil and certain criteria recommendations shall be based upon.

The last major aspect of the quantitative questionnaire may be seen in the importance of including an independent variable that enables advanced statistical analyses of the quantitative questionnaire. In the context of the present evaluation, the most important aspect may be seen in the quality of the analysed dataset itself. It is assumed that experienced investors deliver more important input/information to the modelling of the recommendation system. Therefore, a question about participants' experience is included in the quantitative questionnaire, which is interpreted as independent variable in the analysis phase of the quantitative questionnaire later on.

Ultimately, Table 2.15 depicts the quantitative questionnaire's finalized set of questions and their corresponding response types grouped by question category.

Table 2.15: Finalized set of questions utilized for the quantitative questionnaire

Category	Type	Question
Characteristics of Investors	Likert (Ordinal, 1–5)	Based on which criteria do you decide upon, whether an investment in an early-stage enterprise shall be conducted?
Characteristics of early-stage enterprises	Likert (Ordinal, 1–5)	Which characteristics does an early-stage enterprise need in order for you to consider investing?
	Dichotomous / Binary (Yes/No)	Are you able to predict the success/failure of an early-stage enterprise in the (pre-)seed stage?
Venture Valuation	Likert (Ordinal, 1–5)	Which characteristics of early-stage enterprises are important for venture valuations?
	Likert (Categorical; 1–4)	Due to the fact that early-stage enterprises of the (pre-) seed stage lack a historic track record of business activities, a valuation is hardly feasible or completely impossible. Therefore, especially business angels utilize self-defined best practices and rules of thumb as valuation methods, which are already discussed by scientific literature. Which of the following valuation methods do you use?
Recommender System (Platform)	Likert (Ordinal, 1–5)	Which functionality should a platform for recommending early-stage enterprises to investors provide in order to offer additional value to you?
	Likert (Ordinal, 1–5)	According to which criteria shall recommendations be generated?

2.3.2 Quantitative Questionnaire Results

The quantitative questionnaire's main goal was to quantize knowledge gained by the qualitative expert interviews. In particular, it is the (data)model of the recommender system that is affected by the outcome of this very questionnaire, that is, design of the model and model parameters of the recommender system are shaped according to the elaborated characteristics. In the course of this subsection, details and challenges of the the present questionnaire are discussed, followed by the analysis and evaluation of each question.

In contrast to the qualitative expert interviews, the response rate of participants taking the questionnaire lasts at a considerably high percentage of ~52.2%, that is, 25 out of 47 persons (it shall be noted that the results of all 25 persons are utilized in statistical tests later on). However, finding participants who conform to the stated participant profile/type, again, turned out to be a non-trivial endeavour. In fact, solely relying on e-mail- or telephone communication did not turn out to gain the anticipated results. As a consequence, networking and personal meetings needed to be utilized in order to increase the number of participants. Particularly, two events played a key factor in raising the number of participants: The *AWS*[18] *Greenworth Batch* and the *Puls4 4GAMECHANGER festival*[19]. In the course of these events—both networking events between new early-stage enterprises and investors—investors were introduced to the topic of the present work and asked to participate in the quantitative questionnaire. Through the exchange of business cards, the questionnaire—accessible on-line via the *Google Forms*[20] service—was forwarded to the corresponding investors via e-mail.

The following passages analyse and evaluate the results of the quantitative questionnaire grouped by question. For the purpose of consistency to the present work, questions, sub-questions and answer sets were translated from German.

Question 1: Based on which criteria do you decide upon, whether an investment in an early-stage enterprise shall be conducted?

The main objective of this question was to gain insights on the importance of certain criteria the investor bases investment decisions on. The remainder of this question is stated as follows: The analysis references the Likert sub-question indexes instead of their corresponding descriptions (the reader is referred to the representation of index / sub-question mappings listed below). Finally, the analysed data is interpreted in the evaluation passage.

Subquestions

- SQ1 Recommendations (e.g. by investors)
- SQ2 Historic investment decisions
- SQ3 Relationship to entrepreneur(s)
- SQ4 Industry sector
- SQ5 Experience of entrepreneur(s)
- SQ6 Return on investment vs. risk
- SQ7 Market research
- SQ8 Valuations of ventures
- SQ9 Geographical business location
- SQ10 Market of the early-stage enterprise (geographical)

[18] AWS: Austria Wirtschaftsservice – https://www.aws.at/
[19] Puls4 4GAMECHANGER festival: https://www.puls4.com/4GAMECHANGER
[20] Google Forms: https://www.google.com/forms/about/

Analysis In the course of this passage, the collected data of the present question is analysed according to the following categories: *descriptive statistics*, *reliability* and *statistical tests* of the dataset.

Descriptive Statistics quantitatively summarize and characterize the present data. Due to fact that the dataset is based on an ordinal scale, it is not possible to calculate a degree of difference on a relative basis. However, ranking of the responses according to the question's underlying order is possible. Therefore, the *median* needs to be adduced as the *measure of central tendency*, rather than the *mean*. The reader is referred to Table 2.16 for summarized descriptive statistics of the dataset. Figure 2.6 visualizes an overall plot of participants' responses grouped by the answer set and ordered by the percentage of number of responses in the corresponding answer set in descending order. Additionally, the attached histogram visualizes missing- and completed answers per sub-question.

Table 2.16: Question 1 – Descriptive Statistics

SQ	Group	N	N (valid)	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
SQ1	Overall	25	25	3.56	0.961	2	3	3	4	5
	Yes	14	14	3.429	0.938	2	3	3	4	5
	No	7	7	3.143	0.69	2	3	3	3.5	4
SQ2	Overall	25	24	2.958	0.908	1	2	3	3.25	5
	Yes	14	14	3	0.961	2	2	3	3.75	5
	No	7	7	3	0.577	2	3	3	3	4
SQ3	Overall	25	23	2.87	1.325	1	2	3	4	5
	Yes	14	13	2.769	1.363	1	2	2	4	5
	No	7	7	3.429	1.272	2	2.5	3	4.5	5
SQ4	Overall	25	25	3.92	1.038	1	3	4	5	5
	Yes	14	14	3.929	1.328	1	3	4.5	5	5
	No	7	7	3.857	0.378	3	4	4	4	4
SQ5	Overall	25	25	4.12	0.881	2	4	4	5	5
	Yes	14	14	4	0.877	2	4	4	4.75	5
	No	7	7	4.286	0.951	3	3.5	5	5	5
SQ6	Overall	25	24	4.125	0.85	2	4	4	5	5
	Yes	14	14	4.071	0.917	2	4	4	5	5
	No	7	6	4	0.894	3	3.25	4	4.75	5
SQ7	Overall	25	25	3.68	1.145	2	3	4	5	5
	Yes	14	14	3.5	1.345	2	2	3.5	5	5
	No	7	7	4.143	0.378	4	4	4	4	5
SQ8	Overall	25	24	3.458	1.103	1	3	3	4	5

To be continued…

…continued from previous page

SQ	Group	N	N (valid)	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
	Yes	14	14	3.5	1.225	1	3	3	4.75	5
	No	7	6	3.333	1.211	2	2.25	3.5	4	5
SQ9	Overall	25	25	2.92	1.256	1	2	3	4	5
	Yes	14	14	2.571	1.158	1	2	2.5	3.75	4
	No	7	7	3.286	1.496	1	2.5	3	4.5	5
SQ10	Overall	25	25	3.52	1.194	1	3	4	4	5
	Yes	14	14	3.429	1.222	1	3	4	4	5
	No	7	7	3.429	1.134	2	2.5	4	4	5

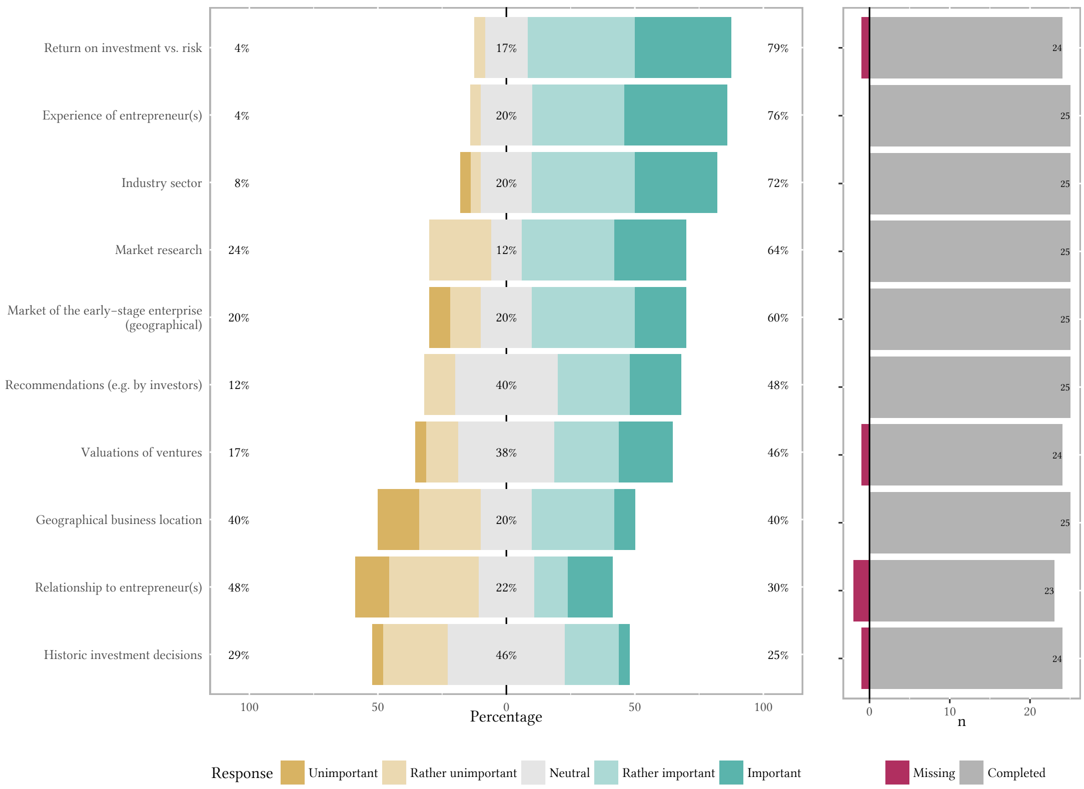

Figure 2.6: Question 1 – Plot (incl. histogram)

Reliability in terms of the internal consistency among participants' responses to the sub-questions is measured by utilizing *Cronbach's alpha* statistic, which indicates a std. alpha value of $\alpha = 0.66$. The reader is referred to appendix B.1 for a detailed analysis of reliability.

Statistical Tests are utilized for ascertaining whether the present sub-questions are normally distributed and conducting research on a possible applicability to the underlying (data)model of the recommender system. A test for normal distribution of participants' responses per sub-question is conducted utilizing the *Shapiro-Wilk Test* with the following hypotheses:

(i) H0: Participants' responses are normally distributed

(ii) H1: Participants' responses are not normally distributed

Table 2.17 shows that the ρ values calculated by the Shapiro-Wilk test are smaller than the significance level $\alpha = 0.05$ among *all* sub-questions. Therefore, the H0 hypothesis of each sub-question needs to be rejected, that is, no population of a corresponding sub-question is normally distributed.

Regarding research on the underlying (data)model of the recommender system, there are basically two questions to be analysed:

(i) Is there statistical significance about the fact that participants rated a certain sub-question either *Rather important* or *Important*?

  (a) Wilcoxon Signed Rank Test: Test whether the median m of a certain sub-question is greater than three.

  (b) H0: $m \leq 3$

  (c) H1: $m > 3$

  (d) Significance level: 97.5% ($\alpha = 0.025$)

(ii) Is there statistical significance about the fact that experienced- and inexperienced investors have a different opinion on a certain sub-question?

  (a) Wilcoxon Rank Sum Test: Test whether the location shift a between the distributions of experienced- and inexperienced investors differs significantly from 0.

    - H0: $a = 0$, H1: $a \neq 0$, that is, experienced investors rank the corresponding sub-questions *differently* than inexperienced investors.
    - H0: $a \geq 0$, H1: $a < 0$, that is, experienced investors rank the corresponding sub-questions *lower* than inexperienced investors.
    - H0: $a \leq 0$, H1: $a > 0$, that is, experienced investors rank the corresponding sub-questions *higher* than inexperienced investors.

  (b) Significance levels:

    - Two-tailed test: 95% ($\alpha = 0.05$)
    - One-tailed tests: 97.5% ($\alpha = 0.025$)

As indicated by Table 2.17, the following sub-questions grouped by the corresponding tests are statistically significant—that is, the ρ values calculated by the tests are smaller than the significance level $\alpha = 0.05$ ($\alpha = 0.025$ respectively) among the corresponding sub-questions—and therefore, the H0 hypothesis needed to be rejected:

(i) Wilcoxon Signed Rank Test: *SQ1, SQ4, SQ5, SQ6, SQ7*

(ii) Wilcoxon Rank Sum Test: *None*

Table 2.17: Question 1 – Statistical Tests

SQ	Sh.-W. T.		Wilcox. Signed Rank T.		Wilcox. Rank Sum T.			
	W	ρ	V	ρ	W	$\rho\ (a \neq 0)$	$\rho\ (a < 0)$	$\rho\ (a > 0)$
SQ1	0.88	0.006	103.5	0.006	57	0.548	0.752	0.274
SQ2	0.91	0.028	42.5	0.604	46.5	0.872	0.436	0.595
SQ3	0.89	0.015	78	0.641	32	0.288	0.144	0.874
SQ4	0.85	0.001	188	0.001	58.5	0.48	0.784	0.24
SQ5	0.83	0.001	204.5	0	39.5	0.475	0.238	0.786
SQ6	0.83	0.001	204	0	45	0.827	0.62	0.413
SQ7	0.83	0.001	205	0.004	38.5	0.434	0.217	0.805
SQ8	0.91	0.031	92.5	0.03	46	0.765	0.65	0.382
SQ9	0.9	0.022	95	0.659	34.5	0.285	0.142	0.874
SQ10	0.88	0.008	155	0.027	50	0.969	0.547	0.484

Evaluation In analogy to the previous passage, the findings of the analysis will be evaluated according to *reliability*- and *statistical tests* of the dataset.

As pointed out during analysis, reliability of the present question is stated as the std. alpha value $\alpha = 0.66$, which is slightly less than being *acceptable*. In particular, this outcome means that the internal consistency among participants' responses to the present sub-question lies at the edge of being *questionable* or *acceptable* respectively. As for the present work, the internal consistency is considered *accepted* under the condition of extending the size of the test sample (participants) in future research [Cronbach, 1951, p. 323].

The fact that none of the sub-questions are normally distributed indicates that corresponding parametrized statistical tests can not be applied. Therefore, the decision on utilizing non-parametrized statistical tests for answering the following questions was correct.

The question whether there is statistical significance about the fact that participants rated a certain sub-question either *Rather important* or *Important* holds for the following sub-questions:

- SQ1 – Recommendations (e.g. by investors)
- SQ4 – Industry sector
- SQ5 – Experience of entrepreneur(s)
- SQ6 – Return on investment vs. risk
- SQ7 – Market research

Therefore, criteria indicated by these sub-questions will be considered for the (data)model of the recommender system.

The question whether there is statistical significance about the fact that experienced- and inexperienced investors rated a certain sub-question differently—and in particular, whether experienced investors rated the corresponding sub-question lower/higher than their inexperienced counterparts—does not hold for any of the sub-questions. Thus, there is no indication that the median or distribution of values of experienced investors are statistically different from those of inexperienced investors. As a consequence, no information in this regard is considered for the (data)model of the recommender system.

Question 2: Which characteristics does an early-stage enterprise need in order for you to consider investing?

The main objective of this question was to gain insights on the importance of certain early-stage enterprise characteristics that need to be fulfilled in order to make an investor consider investing. The remainder of this question is stated as follows: The analysis references the Likert sub-question indexes instead of their corresponding descriptions (the reader is referred to the representation of index / sub-question mappings listed below). Finally, the analysed data is interpreted in the evaluation passage.

Subquestions

SQ1 Team: Former experience as CEO

SQ2 Team: Former experience as COO, CFO, CTO

SQ3 Team: Existent knowledge to implement the product idea

SQ4 Team: Founder team consists of min. 2 persons

SQ5 Team: Founder is willing to step back (if needed)

SQ6 Team: Own funds at time of foundation

SQ7 Product idea elaborated (prototype implemented)

SQ8 Product idea elaborated (prototype not implemented)

SQ9 Product idea available and rudimentarily elaborated

SQ10 Product idea protected by patents

SQ11 Industry sector is not saturated. Market entry of the product idea possible

SQ12 Market analysis / Industry sector analysis / venture valuation available

SQ13 Plausibility of the enterprise formation

Analysis In the course of this passage, the collected data of the present question is analysed according to the following categories: *descriptive statistics*, *reliability* and *statistical tests* of the dataset.

Descriptive Statistics quantitatively summarize and characterize the present data. Due to the fact that the dataset is based on an ordinal scale, it is not possible to calculate a degree of difference on a relative basis. However, ranking of the responses according to the question's underlying order is possible. Therefore, the *median* needs to be adduced as the *measure of central tendency*, rather than the *mean*. The reader is referred to Table 2.18 for summarized descriptive statistics of the dataset. Figure 2.7 visualizes an overall plot of participants' responses grouped by the answer set and ordered by the percentage of number of responses in the corresponding answer set in descending order. Additionally, the attached histogram visualizes missing- and completed answers per sub-question.

Table 2.18: Question 2 – Descriptive Statistics

SQ	Group	N	N (valid)	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
SQ1	Overall	25	25	3.12	0.971	1	2	3	4	5
	Yes	14	14	2.786	0.975	1	2	3	3.75	4
	No	7	7	3.714	0.756	3	3	4	4	5
SQ2	Overall	25	25	3.16	1.028	1	2	3	4	5
	Yes	14	14	2.929	1.141	1	2	3	4	5
	No	7	7	3.429	0.976	2	3	3	4	5
SQ3	Overall	25	25	3.72	1.1	1	3	4	4	5
	Yes	14	14	3.5	1.16	1	3	4	4	5
	No	7	7	3.857	1.215	2	3	4	5	5
SQ4	Overall	25	25	3.56	1.261	1	3	4	5	5
	Yes	14	14	3.357	1.151	2	2.25	3	4	5
	No	7	7	3.714	1.704	1	2.5	5	5	5
SQ5	Overall	25	24	2.833	0.963	1	2	3	3.25	5
	Yes	14	14	2.571	1.016	1	2	2	3	5
	No	7	6	3	0.894	2	2.25	3	3.75	4
SQ6	Overall	25	25	2.72	1.37	1	2	2	4	5
	Yes	14	14	2.429	1.222	1	2	2	3	5
	No	7	7	3.143	1.676	1	2	3	4.5	5
SQ7	Overall	25	25	3.64	1.114	1	3	4	4	5
	Yes	14	14	4	1.109	2	3.25	4	5	5

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SQ	Group	N	N (valid)	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
	No	7	7	2.857	1.069	1	2.5	3	3.5	4
SQ8	Overall	25	25	3.36	1.186	1	3	3	4	5
	Yes	14	14	3.429	1.158	1	3	3	4	5
	No	7	7	3.143	1.574	1	2	3	4.5	5
SQ9	Overall	25	25	3.6	1.323	1	2	4	5	5
	Yes	14	14	3.429	1.453	1	2	3.5	5	5
	No	7	7	3.571	1.272	2	2.5	4	4.5	5
SQ10	Overall	25	25	3.44	1.193	1	3	3	4	5
	Yes	14	14	3.5	1.345	1	2.25	4	4.75	5
	No	7	7	3.143	0.9	2	3	3	3	5
SQ11	Overall	25	25	4	0.816	2	4	4	4	5
	Yes	14	14	4	0.784	2	4	4	4	5
	No	7	7	3.714	0.951	2	3.5	4	4	5
SQ12	Overall	25	25	3.44	1.121	1	3	3	4	5
	Yes	14	14	3.357	1.216	1	3	3	4	5
	No	7	7	3.286	0.756	2	3	3	4	4
SQ13	Overall	25	25	4.24	1.2	1	4	5	5	5
	Yes	14	14	4.214	1.188	1	4	5	5	5
	No	7	7	3.857	1.464	1	3.5	4	5	5

Reliability in terms of the internal consistency among participants' responses to the sub-questions is measured by utilizing *Cronbach's alpha* statistic, which indicates a std. alpha value of $\alpha = 0.73$. The reader is referred to appendix B.2 for a detailed analysis of reliability.

Statistical Tests are utilized for ascertaining whether the present sub-questions are normally distributed and conducting research on a possible applicability to the underlying (data)model of the recommender system. A test for normal distribution of participants' responses per sub-question is conducted utilizing the *Shapiro-Wilk Test* with the following hypotheses:

(i) H0: Participants' responses are normally distributed

(ii) H1: Participants' responses are not normally distributed

Table 2.19 shows that the ρ values calculated by the Shapiro-Wilk test are smaller than the significance level $\alpha = 0.05$ among *all* sub-questions. Therefore, the H0 hypothesis of each sub-question needs to be rejected, that is, no population of a corresponding sub-question is normally distributed.

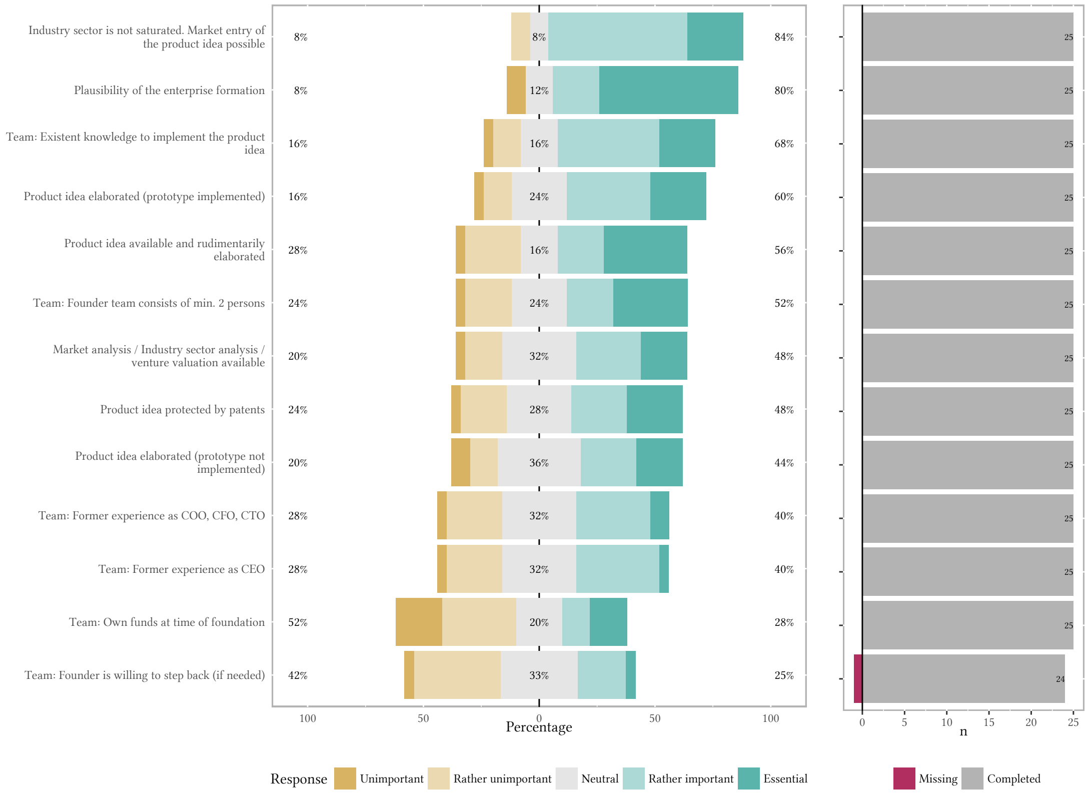

Figure 2.7: Question 2 – Plot (incl. histogram)

Regarding research on the underlying (data)model of the recommender system, there are basically two questions to be analysed:

(i) Is there statistical significance about the fact that participants rated a certain sub-question either *Rather important* or *Essential*?

(a) Wilcoxon Signed Rank Test: Test whether the median m of a certain sub-question is greater than three.

(b) H0: $m \leq 3$

(c) H1: $m > 3$

(d) Significance level: 97.5% ($\alpha = 0.025$)

(ii) Is there statistical significance about the fact that experienced- and inexperienced investors have a different opinion on a certain sub-question?

(a) Wilcoxon Rank Sum Test: Test whether the location shift a between the distributions of experienced- and inexperienced investors differs significantly from 0.

- H0: $a = 0$, H1: $a \neq 0$, that is, experienced investors rank the corresponding sub-questions *differently* than inexperienced investors.
- H0: $a \geq 0$, H1: $a < 0$, that is, experienced investors rank the corresponding sub-questions *lower* than inexperienced investors.
- H0: $a \leq 0$, H1: $a > 0$, that is, experienced investors rank the corresponding sub-questions *higher* than inexperienced investors.

(b) Significance levels:

- Two-tailed test: 95% ($\alpha = 0.05$)
- One-tailed tests: 97.5% ($\alpha = 0.025$)

As indicated by Table 2.19, the following sub-questions grouped by the corresponding tests are statistically significant—that is, the ρ values calculated by the tests are smaller than the significance level $\alpha = 0.05$ ($\alpha = 0.025$ respectively) among the corresponding sub-questions—and therefore, the H0 hypothesis needed to be rejected:

(i) Wilcoxon Signed Rank Test: *SQ3, SQ4, SQ7, SQ9, SQ11, SQ13*

(ii) Wilcoxon Rank Sum Test: *SQ7 ($a > 0$)*

Table 2.19: Question 2 – Statistical Tests

SQ	Sh.-W. T.		Wilcox. Signed Rank T.		Wilcox. Rank Sum T.			
	W	ρ	V	ρ	W	ρ $(a \neq 0)$	ρ $(a < 0)$	ρ $(a > 0)$
SQ1	0.9	0.016	88.5	0.277	24	0.056	0.028	0.977
SQ2	0.92	0.04	92	0.223	36.5	0.354	0.177	0.843
SQ3	0.87	0.004	190.5	0.004	40.5	0.535	0.267	0.758
SQ4	0.88	0.006	147.5	0.016	40	0.512	0.256	0.768
SQ5	0.9	0.018	53	0.808	30	0.312	0.156	0.864
SQ6	0.88	0.008	82	0.817	36	0.339	0.17	0.849
SQ7	0.89	0.014	154.5	0.007	76	0.041	0.983	0.021
SQ8	0.91	0.028	95	0.079	55	0.672	0.691	0.336
SQ9	0.85	0.002	178.5	0.013	47	0.908	0.454	0.577
SQ10	0.9	0.022	126	0.036	58.5	0.488	0.779	0.244
SQ11	0.78	0	258	0	57.5	0.492	0.78	0.246
SQ12	0.91	0.036	114.5	0.033	51	0.907	0.577	0.453
SQ13	0.68	0	225	0	56.5	0.569	0.742	0.285

Evaluation In analogy to the previous passage, the findings of the analysis will be evaluated according to *reliability*- and *statistical tests* of the dataset.

As pointed out during analysis, reliability of the present question is stated as the std. alpha value $\alpha = 0.73$, which is considered *acceptable*. In particular, this outcome means that the internal consistency among participants' responses to the present sub-question is *acceptable*. Therefore, there are no objections—in terms of reliability—in utilizing the present dataset for further statistical analysis.

The fact that none of the sub-questions are normally distributed indicates that corresponding parametrized statistical tests can not be applied. Therefore, the decision on utilizing non-parametrized statistical tests for answering the following questions was correct.

The question whether there is statistical significance about the fact that participants rated a certain sub-question either *Rather important* or *Essential* holds for the following sub-questions:

- SQ3 – Team: Existent knowledge to implement the product idea
- SQ4 – Team: Founder team consists of min. 2 persons
- SQ7 – Product idea elaborated (prototype implemented)
- SQ9 – Product idea available and rudimentarily elaborated
- SQ11 – Industry sector is not saturated. Market entry of the product idea possible
- SQ13 – Plausibility of the enterprise formation

Therefore, characteristics of early-stage enterprises indicated by these sub-questions will be considered for the (data)model of the recommender system.

The question whether there is statistical significance about the fact that experienced- and inexperienced investors rated a certain sub-question differently—and in particular, whether experienced investors rated the corresponding sub-question lower/higher than their inexperienced counterparts—holds for the following sub-question:

- SQ7 – Product idea elaborated (prototype implemented) *($a > 0$)*

Due to the fact that experienced investors ranked sub-question SQ7 higher than their inexperienced counterparts, the justification for considering SQ7 in the model building phase of the recommender system is further supported by this very test.

Question 3: Are you able to predict the success/failure of an early-stage enterprise in the (pre-)seed stage?

The main objective of this question was to gain insights on the fact whether a participant feels capable of predicting the success or failure of an early-stage enterprise while still lasting in the (pre-)seed stage. Therefore, this question was utilized as an independent variable in order to enable splitting of the data. Analogously to the previous questions, the following passages analyse and evaluate the present question.

Analysis In the course of this passage, the collected data of the present question is summarized utilizing descriptive statistics.

Descriptive Statistics quantitatively summarize and characterize the present data. Due to the fact that the dataset is based on a dichotomous scale, descriptive statistics are limited to depicting the distribution of *Yes / No*- and missing values (the reader is referred to Table 2.20 for summarized descriptive statistics of the dataset).

Table 2.20: Question 3 – Descriptive Statistics

Q3	N
Yes	14
No	7
NA's	4

Evaluation In analogy to the previous passage, the findings of the analysis will be evaluated based on descriptive statistics. As pointed out by Table 2.20, the most frequent response was the value *Yes*, which, in fact, turned out to be quite surprising to the author. In particular, the ratio between *Yes/No* answers reached a considerably high $2 : 1$ (not considering missing values). Thus, the majority of participants consider themselves capable of determining the success/failure of early-stage enterprises during the (pre-)seed stage. In the course of the remaining questions, statistical tests will determine whether participants' responses differ between experienced- and inexperienced investors.

Question 4: Which characteristics of early-stage enterprises are important for venture valuations?

The main objective of this question was to gain insights on the importance of certain early-stage enterprise characteristics needed in the course of a valuation. The remainder of this question is stated as follows: The analysis references the Likert sub-question indexes instead of their corresponding descriptions (the reader is referred to the representation of index / sub-question mappings listed below). Finally, the analysed data is interpreted in the evaluation passage.

Subquestions

SQ1 Opportunity (market situation, revenue in 5 years)

SQ2 Maturity level of the product idea

SQ3 Customer acceptance of the product idea

SQ4 Equity capital / financial assets of the founders

SQ5 Industry structure (market entry barriers, market growth)

SQ6 Competition

SQ7 Number of founders > 1

SQ8 Experience of the founder team

SQ9 Founders already have experience in founding- and running early-stage enterprises

Analysis In the course of this passage, the collected data of the present question is analysed according to the following categories: *descriptive statistics*, *reliability* and *statistical tests* of the dataset.

Descriptive Statistics quantitatively summarize and characterize the present data. Due to the fact that the dataset is based on an ordinal scale, it is not possible to calculate a degree of difference on a relative basis. However, ranking of the responses according to the question's underlying order is possible. Therefore, the *median* needs to be adduced as the *measure of central tendency*, rather than the *mean*. The reader is referred to Table 2.21 for summarized descriptive statistics of the dataset. Figure 2.8 visualizes an overall plot of participants' responses grouped by the answer set and ordered by the percentage of number of responses in the corresponding answer set in descending order. Additionally, the attached histogram visualizes missing- and completed answers per sub-question.

Table 2.21: Question 4 – Descriptive Statistics

SQ	Group	N	N (valid)	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
SQ1	Overall	25	25	4.08	1.187	2	3	5	5	5
	Yes	14	14	3.929	1.141	2	3	4	5	5
	No	7	7	3.857	1.464	2	2.5	5	5	5
SQ2	Overall	25	25	3.64	1.15	1	3	4	4	5
	Yes	14	14	3.571	1.089	2	3	4	4	5
	No	7	7	3.429	1.512	1	2.5	4	4.5	5
SQ3	Overall	25	25	4.08	1.038	1	4	4	5	5
	Yes	14	14	4.214	0.893	2	4	4	5	5
	No	7	7	3.714	1.38	1	3.5	4	4.5	5
SQ4	Overall	25	25	2.44	1.044	1	2	2	3	5
	Yes	14	14	2.286	0.726	1	2	2	3	3
	No	7	7	2.857	1.574	1	2	2	4	5
SQ5	Overall	25	25	4.04	0.79	2	4	4	5	5
	Yes	14	14	4	0.877	2	4	4	4.75	5
	No	7	7	3.857	0.69	3	3.5	4	4	5

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SQ	Group	N	N (valid)	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
SQ6	Overall	25	25	3.84	0.8	2	4	4	4	5
	Yes	14	14	3.786	1.051	2	3	4	4.75	5
	No	7	7	3.857	0.378	3	4	4	4	4
SQ7	Overall	25	23	3.043	1.296	1	2	3	4	5
	Yes	14	13	3.154	1.345	1	2	3	4	5
	No	7	6	2.5	1.225	2	2	2	2	5
SQ8	Overall	25	24	3.833	0.816	2	3	4	4	5
	Yes	14	14	3.857	0.949	2	3	4	4.75	5
	No	7	6	3.5	0.548	3	3	3.5	4	4
SQ9	Overall	25	24	3.25	1.152	1	2	3	4	5
	Yes	14	14	3.429	1.158	2	2.25	3.5	4	5
	No	7	6	2.833	1.329	1	2.25	3	3	5

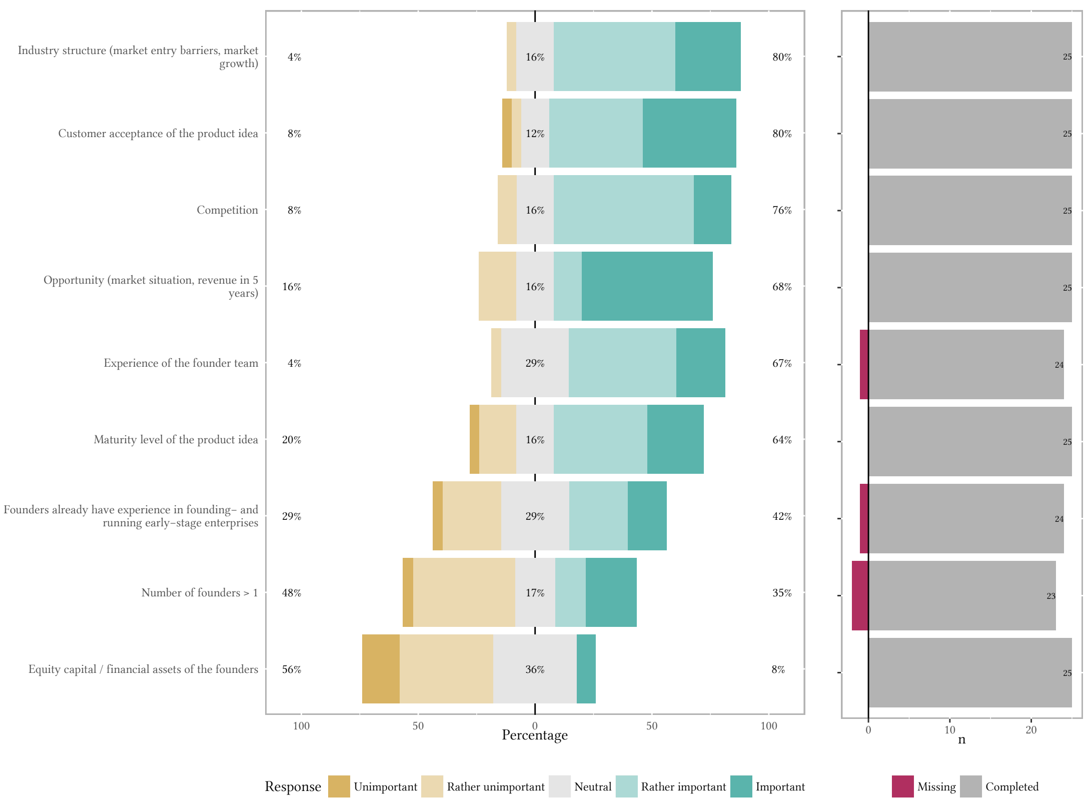

Figure 2.8: Question 4 – Plot (incl. histogram)

Reliability in terms of the internal consistency among participants' responses to the sub-questions is measured by utilizing *Cronbach's alpha* statistic, which indicates a std. alpha value of $\alpha = 0.68$. The reader is referred to appendix B.4 for a detailed analysis of reliability.

Statistical Tests are utilized for ascertaining whether the present sub-questions are normally distributed and conducting research on a possible applicability to the underlying (data)model of the recommender system. A test for normal distribution of participants' responses per sub-question is conducted utilizing the *Shapiro-Wilk Test* with the following hypotheses:

(i) H0: Participants' responses are normally distributed

(ii) H1: Participants' responses are not normally distributed

Table 2.22 shows that the ρ values calculated by the Shapiro-Wilk test are smaller than the significance level $\alpha = 0.05$ among *all* sub-questions. Therefore, the H0 hypothesis of each sub-question needs to be rejected, that is, no population of a corresponding sub-question is normally distributed.

Regarding research on the underlying (data)model of the recommender system, there are basically two questions to be analysed:

(i) Is there statistical significance about the fact that participants rated a certain sub-question either *Rather important* or *Important*?
   - (a) Wilcoxon Signed Rank Test: Test whether the median m of a certain sub-question is greater than three.
   - (b) H0: $m \leq 3$
   - (c) H1: $m > 3$
   - (d) Significance level: 97.5% ($\alpha = 0.025$)

(ii) Is there statistical significance about the fact that experienced- and inexperienced investors have a different opinion on a certain sub-question?
   - (a) Wilcoxon Rank Sum Test: Test whether the location shift a between the distributions of experienced- and inexperienced investors differs significantly from 0.
     - H0: $a = 0$, H1: $a \neq 0$, that is, experienced investors rank the corresponding sub-questions *differently* than inexperienced investors.
     - H0: $a \geq 0$, H1: $a < 0$, that is, experienced investors rank the corresponding sub-questions *lower* than inexperienced investors.
     - H0: $a \leq 0$, H1: $a > 0$, that is, experienced investors rank the corresponding sub-questions *higher* than inexperienced investors.
   - (b) Significance levels:
     - Two-tailed test: 95% ($\alpha = 0.05$)

- One-tailed tests: 97.5% ($\alpha = 0.025$)

As indicated by Table 2.22, the following sub-questions grouped by the corresponding tests are statistically significant—that is, the ρ values calculated by the tests are smaller than the significance level $\alpha = 0.05$ ($\alpha = 0.025$ respectively) among the corresponding sub-questions—and therefore, the H0 hypothesis needed to be rejected:

(i) Wilcoxon Signed Rank Test: *SQ1, SQ2, SQ3, SQ5, SQ6, SQ8*

(ii) Wilcoxon Rank Sum Test: *None*

Table 2.22: Question 4 – Statistical Tests

SQ	Sh.-W. T.		Wilcox. Signed Rank T.		Wilcox. Rank Sum T.			
	W	ρ	V	ρ	W	$\rho\ (a \neq 0)$	$\rho\ (a < 0)$	$\rho\ (a > 0)$
SQ1	0.74	0	215	0	48.5	1	0.5	0.532
SQ2	0.88	0.006	183	0.008	50	0.969	0.546	0.485
SQ3	0.8	0	230	0	59.5	0.423	0.811	0.211
SQ4	0.85	0.001	27	0.987	43	0.662	0.331	0.697
SQ5	0.83	0.001	223.5	0	56	0.596	0.73	0.298
SQ6	0.81	0	213	0	49.5	1	0.532	0.5
SQ7	0.84	0.002	103.5	0.369	51.5	0.262	0.888	0.131
SQ8	0.87	0.004	146.5	0	52.5	0.381	0.832	0.191
SQ9	0.91	0.043	99	0.138	53	0.373	0.836	0.186

Evaluation In analogy to the previous passage, the findings of the analysis will be evaluated according to *reliability*- and *statistical tests* of the dataset.

As pointed out during analysis, reliability of the present question is stated as the std. alpha value $\alpha = 0.68$, which is slightly less than being *acceptable*. In particular, this outcome means that the internal consistency among participants' responses to the present sub-question lies at the edge of being *questionable* or *acceptable* respectively. As for the present work, the internal consistency is considered *accepted* under the condition of extending the size of the test sample (participants) in future research [Cronbach, 1951, p. 323].

The fact that none of the sub-questions are normally distributed indicates that corresponding parametrized statistical tests can not be applied. Therefore, the decision on utilizing non-parametrized statistical tests for answering the following questions was correct.

The question whether there is statistical significance about the fact that participants rated a certain sub-question either *Rather important* or *Important* holds for the following sub-questions:

- SQ1 – Opportunity (market situation, revenue in 5 years)
- SQ2 – Maturity level of the product idea
- SQ3 – Customer acceptance of the product idea
- SQ5 – Industry structure (market entry barriers, market growth)
- SQ6 – Competition
- SQ8 – Experience of the founder team

Therefore, characteristics of early-stage enterprises indicated by these sub-questions will be considered for the (data)model of the recommender system.

The question whether there is statistical significance about the fact that experienced- and inexperienced investors rated a certain sub-question differently—and in particular, whether experienced investors rated the corresponding sub-question lower/higher than their inexperienced counterparts—does not hold for any of the sub-questions. Thus, there is no indication that the median or distribution of values of experienced investors are statistically different from those of inexperienced investors. As a consequence, no information in this regard is considered for the (data)model of the recommender system.

Question 5: Due to the fact that early-stage enterprises of the (pre-) seed stage lack a historic track record of business activities, a valuation is hardly feasible or completely impossible. Therefore, especially business angels utilize self-defined best practices and rules of thumb as valuation methods, which are already discussed by scientific literature. Which of the following valuation methods do you use?

The main objective of this question was to gain insights on the fact whether investors *utilize* or at least *know* certain venture valuation methods. The remainder of this question is stated as follows: The analysis references the Likert sub-question indexes instead of their corresponding descriptions (the reader is referred to the representation of index / sub-question mappings listed below). Finally, the analysed data is interpreted in the evaluation passage.

Subquestions

SQ1 Scorecard Method

SQ2 Berkus Method

SQ3 Risk Factor Summation Method

SQ4 Venture Capital Method

SQ5 First Chicago Method

SQ6 Real Options Approach

SQ7 Experience

Analysis In the course of this passage, the collected data of the present question is analysed according to the following categories: *descriptive statistics*, *reliability* and *statistical tests* of the dataset.

Descriptive Statistics quantitatively summarize and characterize the present data. Due to the fact that the dataset is based on categories (nominal scale), it is not possible to calculate a degree of difference on a relative basis. Additionally, ranking of the responses according to the question's underlying order is debatable as well, because the categories themselves do not implicate an internal order. Nevertheless, the semantics of the present question allow for an internal ordering as follows:

- Each response type for each answer category is unique, that is, each question is asked in a way that there is no possibility of overlapping answer categories.
- Answer categories represent an ordered factor in terms of importance to the present work, that is, unknown venture valuation techniques are considered less important than a venture valuation technique that is utilized by an investor.

As a consequence, the *median* may be adduced as the *measure of central tendency* (instead of the *mean*). The reader is referred to Table 2.23 for summarized descriptive statistics of the dataset. Figure 2.9 visualizes an overall plot of participants' responses grouped by the answer set and ordered by the percentage of number of responses in the corresponding answer set in descending order. Additionally, the attached histogram visualizes missing- and completed answers per sub-question.

Table 2.23: Question 5 – Descriptive Statistics

SQ	Group	N	N (valid)	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
SQ1	Overall	25	23	2.87	0.869	1	2	3	3.5	4
	Yes	14	12	2.583	0.9	1	2	2.5	3	4
	No	7	7	3	0.816	2	2.5	3	3.5	4
SQ2	Overall	25	22	1.636	0.902	1	1	1	2.75	3
	Yes	14	12	1.75	0.965	1	1	1	3	3
	No	7	7	1.714	0.951	1	1	1	2.5	3
SQ3	Overall	25	22	2.045	1.046	1	1	2	3	4
	Yes	14	12	2.083	1.165	1	1	2	3	4
	No	7	7	2.143	0.9	1	1.5	2	3	3
SQ4	Overall	25	22	2.818	1.097	1	2	3	4	4
	Yes	14	12	2.917	1.084	1	2.75	3	4	4
	No	7	7	2.714	1.113	1	2	3	3.5	4
SQ5	Overall	25	22	1.636	0.902	1	1	1	2.75	3
	Yes	14	12	1.833	0.937	1	1	1.5	3	3
	No	7	7	1.571	0.976	1	1	1	2	3
SQ6	Overall	25	22	2.318	0.945	1	1.25	3	3	4

To be continued…

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SQ	Group	N	N (valid)	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
	Yes	14	12	2.333	0.888	1	1.75	3	3	3
	No	7	7	2.571	1.134	1	2	3	3	4
SQ7	Overall	25	23	3.826	0.491	2	4	4	4	4
	Yes	14	13	3.769	0.599	2	4	4	4	4
	No	7	7	3.857	0.378	3	4	4	4	4

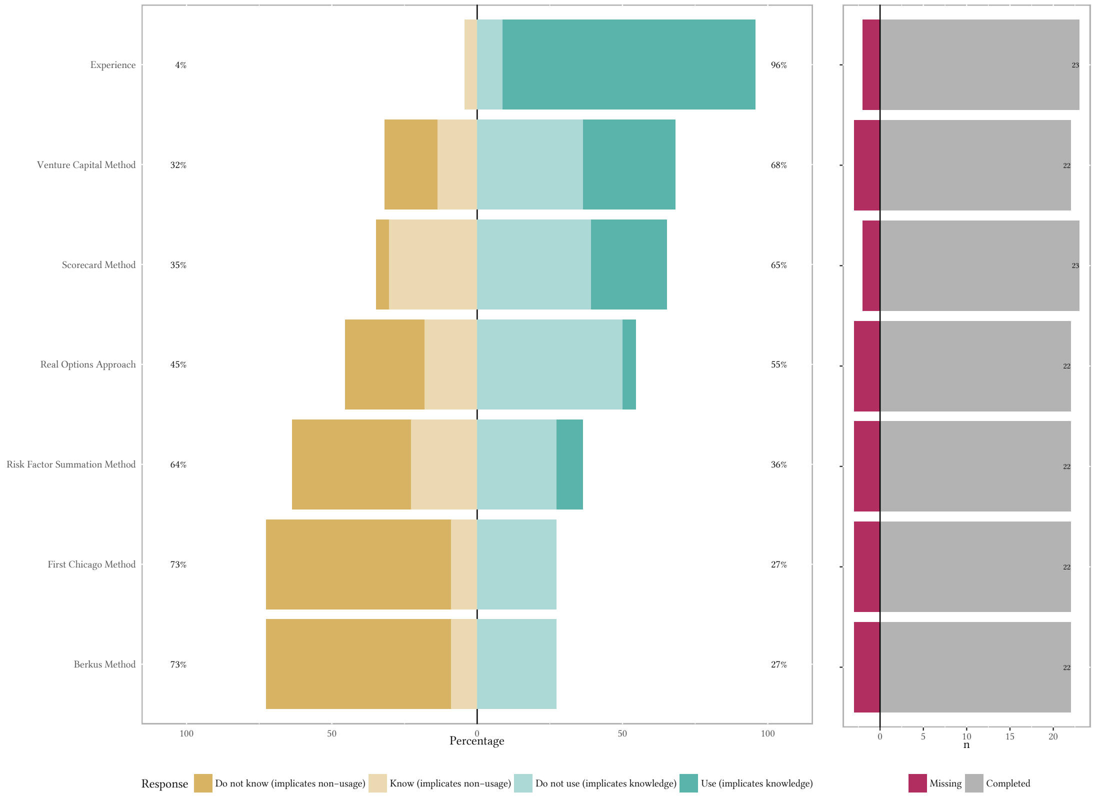

Figure 2.9: Question 5 – Plot (incl. histogram)

Reliability in terms of the internal consistency among participants' responses to the sub-questions is measured by utilizing *Cronbach's alpha* statistic, which indicates a std. alpha value of $\alpha = 0.61$. The reader is referred to appendix B.5 for a detailed analysis of reliability.

Statistical Tests are utilized for ascertaining whether the present sub-questions are normally distributed and conducting research on a possible applicability to the underlying (data)model of the recommender system. A test for normal distribution of participants' responses per sub-question is conducted utilizing the *Shapiro-Wilk Test* with the following hypotheses:

(i) H0: Participants' responses are normally distributed

(ii) H1: Participants' responses are not normally distributed

Table 2.24 shows that the ρ values calculated by the Shapiro-Wilk test are smaller than the significance level $\alpha = 0.05$ among *all* sub-questions. Therefore, the H0 hypothesis of each sub-question needs to be rejected, that is, no population of a corresponding sub-question is normally distributed.

Regarding research on the underlying (data)model of the recommender system, there are basically two questions to be analysed:

(i) Is there statistical significance about the fact that participants did not rate a sub-question with a specific response from the answer set (therefore, the statistically non-significant answer sets are of beneficial utility)?

  (a) Wilcoxon Signed Rank Test: Test whether the median m of a certain sub-question is different as follows:

  - H0: $m = 1$, H1: $m \neq 1$, that is, participants rated a certain sub-question different to answer 1.
  - H0: $m = 2$, H1: $m \neq 2$, that is, participants rated a certain sub-question different to answer 2.
  - H0: $m = 3$, H1: $m \neq 3$, that is, participants rated a certain sub-question different to answer 3.
  - H0: $m = 4$, H1: $m \neq 4$, that is, participants rated a certain sub-question different to answer 4.

  (b) Significance level: 95% ($\alpha = 0.05$)

(ii) Is there statistical significance about the fact that experienced- and inexperienced investors have a different opinion on a certain sub-question?

  (a) Fisher's Exact Test: Test whether the *odds ratio* (OR) between experienced- and inexperienced investors among the distribution of responses differs significantly from 1, that is $OR \neq 1$.

  (b) H0: $OR = 1$

  (c) H1: $OR \neq 1$

  (d) Significance level: 95% ($\alpha = 0.05$)

As for the first question, non-significant answer sets are of interest, because they represent the medians for which the H0 hypothesis can not be rejected and therefore, there is no statistical significance that participants rated different from this median. As a consequence, this particular answer type is chosen for the overall response type among the participants.

The second question, on the other hand, tests whether the odds ratio is significantly different from 1, that is, the two groups of investors responded differently to a certain sub-question. Therefore, statistical significance arises, if the H0 hypothesis is rejected (the ρ value calculated by the test is smaller than the significance level $\alpha = 0.05$). The following listing shows the corresponding sub-question indexes that conform to the aspects mentioned above (grouped by statistical question):

(i) Wilcoxon Signed Rank Test:

- SQ1: $m = 3$
- SQ2: $m = 2$
- SQ3: $m = 2$
- SQ4: $m = 3$
- SQ5: $m = 2$
- SQ6: $m = 2$
- SQ7: $m = 4$

(ii) Fisher's Exact Test:

- *None*

Table 2.24: Question 5 – Statistical Tests

SQ	Sh.-W. T.		Wilcox. Signed Rank T.								Fisher's T.
			$m \neq 1$		$m \neq 2$		$m \neq 3$		$m \neq 4$		
	W	ρ	V	ρ	V	ρ	V	ρ	V	ρ	ρ $(OR^{21} \neq 1)$
SQ1	0.87	0.006	253	0	130.5	0.001	42	0.488	0	0	0.903
SQ2	0.65	0	36	0.01	63	0.077	0	0	0	0	1
SQ3	0.83	0.002	91	0.001	81	0.837	8	0.002	0	0	0.708
SQ4	0.84	0.002	171	0	164	0.004	38.5	0.375	0	0.001	0.831
SQ5	0.65	0	36	0.01	63	0.077	0	0	0	0	0.804
SQ6	0.81	0.001	136	0	117	0.133	3	0.007	0	0	0.686
SQ7	0.41	0	276	0	253	0	220	0	0	0.174	1

Evaluation In analogy to the previous passage, the findings of the analysis will be evaluated according to *reliability*- and *statistical tests* of the dataset.

[21] OR: Odds Ratio

As pointed out during analysis, reliability of the present question is stated as the std. alpha value $\alpha = 0.61$, which is considered *questionable*. In particular, this outcome means that the internal consistency among participants' responses to the present sub-question lies at the edge of being *questionable* or even *poor* respectively. One reason for this score may be seen in the considerably lower amount of sub-questions when compared to the other questions. Cronbach's Alpha statistic generally tends to be lower, if the number of items is low. Therefore, extending the number of items in the present Likert question might increase the score in future research. Another explanation of the low score may be seen in the fact that the sub-questions might be constructed too *broad* or *generic*. In this case, redefinition of the existing questions or adding additional questions might improve the score in future research. However, due to reasons of consistency in the present work, internal consistency of question five is considered *accepted* under the condition of extending the size of the test sample (participants) [Cronbach, 1951, p. 323], and adding additional sub-questions in future research.

The fact that none of the sub-questions are normally distributed indicates that corresponding parametrized statistical tests can not be applied. Therefore, the decision on utilizing non-parametrized statistical tests for answering the following questions was correct.

The statistical test for the question about *which answer type is not significantly different from a certain median* m, needs to be treated with caution. As Table 2.24 visualizes, at least the outcomes for sub-questions *SQ2, SQ5* and *SQ6* need to be further investigated, because of the difference to their calculated medians (see Table 2.23 for a comparison). As Figure 2.9 illustrates, especially sub-questions SQ2 and SQ5 tend to the answer type *Do not know (implicates non-usage)* due to the sheer amount of responses for this answer type. In fact, this particular answer type may even be handled as an outlier. As a consequence, the calculation of the test statistic V for the Wilcoxon Signed Rank Test of $m = 1$ will exclude most of the answer sets, because the subtraction of $X_i - m$ results in 0 for all $X_i = 1$. In the course of the Wilcoxon Signed Rank Test, these corresponding pairs—equalling to zero—are omitted from the analysis, which leads to a drastically reduced effective sample size if there is a considerably large set of X_i fulfilling the constraint $X_i = m$. Subsequently, this behaviour leads to the problem of less facts against resisting of outliers and may not protect against the violation of certain assumptions of the entire test.

An additional problem affecting the assumption of continuity of the distribution for the already mentioned paired differences applies for sub-questions SQ2, SQ5 and especially SQ7: Tied values, that is, clustered paired differences (e.g. $X_i = 4$ for SQ7) that induce problems in calculating the rank of each response.

Due to these reasons, the results of the Wilcoxon Signed Rank Test may not be considered reliable. Therefore, the evaluation and interpretation of this question is additionally conducted by analysing the frequency distributions of each sub-question. In this regard, the most interesting responses may be interpreted for sub-questions *SQ1, SQ2, SQ4, SQ5* and *SQ7*. SQ1 (Scorecard Method) and SQ4 (Venture Capital Method) are the sub-questions that are used the most (excluding SQ1 (Experience), because experience is no de facto venture valuation method). An interesting correlation arises from the fact that SQ2 (Berkus Method) is close to the Scorecard Method from a logical/theoretical and calculation point of view, but—in contrast to the Scorecard

Method—is not known by most participants. Furthermore, SQ7 may be interpreted as *self fulfilling prophecy* that supports the assumption that investors mostly rely on experience and gut instinct, both of which may not be objectively describable.

As a consequence of the mentioned facts and the accompanying support by the literature, the *Scorecard Method* and the *Berkus Method* are chosen to be considered in the (data)model building stage of the recommender system.

The question whether there is statistical significance about the fact that experienced- and inexperienced investors rated a certain sub-question differently, does not hold for any of the sub-questions. Thus, there is no indication that the odds ratio between experienced- and inexperienced investors among the distribution of responses differs significantly from 1. As a consequence, no information in this regard is considered for the (data)model of the recommender system.

Question 6: Which functionality should a platform for recommending early-stage enterprises to investors provide in order to offer additional value to you?

The main objective of this question was to gain insights on the importance of certain characteristics of a potential recommender system for recommending early-stage enterprises to investors. The remainder of this question is stated as follows: The analysis references the Likert sub-question indexes instead of their corresponding descriptions (the reader is referred to the representation of index / sub-question mappings listed below). Finally, the analysed data is interpreted in the evaluation passage.

Subquestions

- SQ1 Visualization of detailed data concerning early-stage enterprises (private area)
- SQ2 Public profile of early-stage enterprises (for measuring customer acceptance)
- SQ3 Investment profile for investors (favourite industry sectors, product interests, investment amount, ...)
- SQ4 Straightforward setup assistant for configuring the investment profile
- SQ5 Filtering early-stage enterprises according to personal preferences
- SQ6 Highlighting of popular early-stage enterprises (high public/investor interest)
- SQ7 Visualization of pre-money valuations of early-stage enterprises
- SQ8 Visualization of investment amount vs. risk
- SQ9 Visualization of the founder team's experience
- SQ10 Smartphone application
- SQ11 E-Mail / Push notification at availability of new interesting early-stage enterprises
- SQ12 Anonymity to visitors of the platform (visitors are neither investors, nor innovators)

Analysis In the course of this passage, the collected data of the present question is analysed according to the following categories: *descriptive statistics*, *reliability* and *statistical tests* of the dataset.

Descriptive Statistics quantitatively summarize and characterize the present data. Due to the fact that the dataset is based on an ordinal scale, it is not possible to calculate a degree of difference on a relative basis. However, ranking of the responses according to the question's underlying order is possible. Therefore, the *median* needs to be adduced as the *measure of central tendency*, rather than the *mean*. The reader is referred to Table 2.25 for summarized descriptive statistics of the dataset. Figure 2.10 visualizes an overall plot of participants' responses grouped by the answer set and ordered by the percentage of number of responses in the corresponding answer set in descending order. Additionally, the attached histogram visualizes missing- and completed answers per sub-question.

Table 2.25: Question 6 – Descriptive Statistics

SQ	Group	N	N (valid)	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
SQ1	Overall	25	24	3.75	1.327	1	2.75	4	5	5
	Yes	14	14	3.571	1.284	2	2.25	3.5	5	5
	No	7	6	3.667	1.751	1	2.5	4.5	5	5
SQ2	Overall	25	24	3.25	1.152	1	2	3	4	5
	Yes	14	14	3.214	1.122	2	2	3	4	5
	No	7	6	3	1.414	1	2.25	3	3.75	5
SQ3	Overall	25	24	3.417	1.06	2	2.75	3.5	4	5
	Yes	14	14	3.714	0.994	2	3	4	4	5
	No	7	6	2.833	1.169	2	2	2.5	3	5
SQ4	Overall	25	24	3.25	1.032	1	2.75	3	4	5
	Yes	14	14	3.571	0.938	2	3	4	4	5
	No	7	6	2.167	0.753	1	2	2	2.75	3
SQ5	Overall	25	24	3.875	1.296	1	3	4	5	5
	Yes	14	14	3.786	1.188	2	3	4	5	5
	No	7	6	3.5	1.761	1	2.25	4	5	5
SQ6	Overall	25	24	3.25	1.113	1	2	3	4	5
	Yes	14	14	3.071	1.269	1	2	3	4	5
	No	7	6	3.5	1.049	2	3	3.5	4	5
SQ7	Overall	25	23	3.739	1.137	2	3	4	5	5
	Yes	14	13	3.615	1.261	2	3	3	5	5
	No	7	6	3.667	1.211	2	3	3.5	4.75	5
SQ8	Overall	25	23	3.13	1.14	1	3	3	4	5
	Yes	14	13	3	1.155	1	3	3	4	5

To be continued…

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SQ	Group	N	N (valid)	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
	No	7	6	3.167	1.472	1	2.25	3.5	4	5
SQ9	Overall	25	23	4	1.128	1	3	4	5	5
	Yes	14	13	3.846	0.987	2	3	4	5	5
	No	7	6	4	1.673	1	3.5	5	5	5
SQ10	Overall	25	22	2.5	1.012	1	2	2	3	5
	Yes	14	12	2.417	0.793	1	2	2	3	4
	No	7	6	3	1.414	1	2.25	3	3.75	5
SQ11	Overall	25	24	3.083	1.248	1	2	3.5	4	5
	Yes	14	14	3.5	1.16	1	3	4	4	5
	No	7	6	2.5	1.225	1	2	2	3.5	4
SQ12	Overall	25	24	3.5	1.18	1	3	3.5	4.25	5
	Yes	14	14	3.429	1.342	1	2.25	3.5	4.75	5
	No	7	6	3.167	0.983	2	3	3	3	5

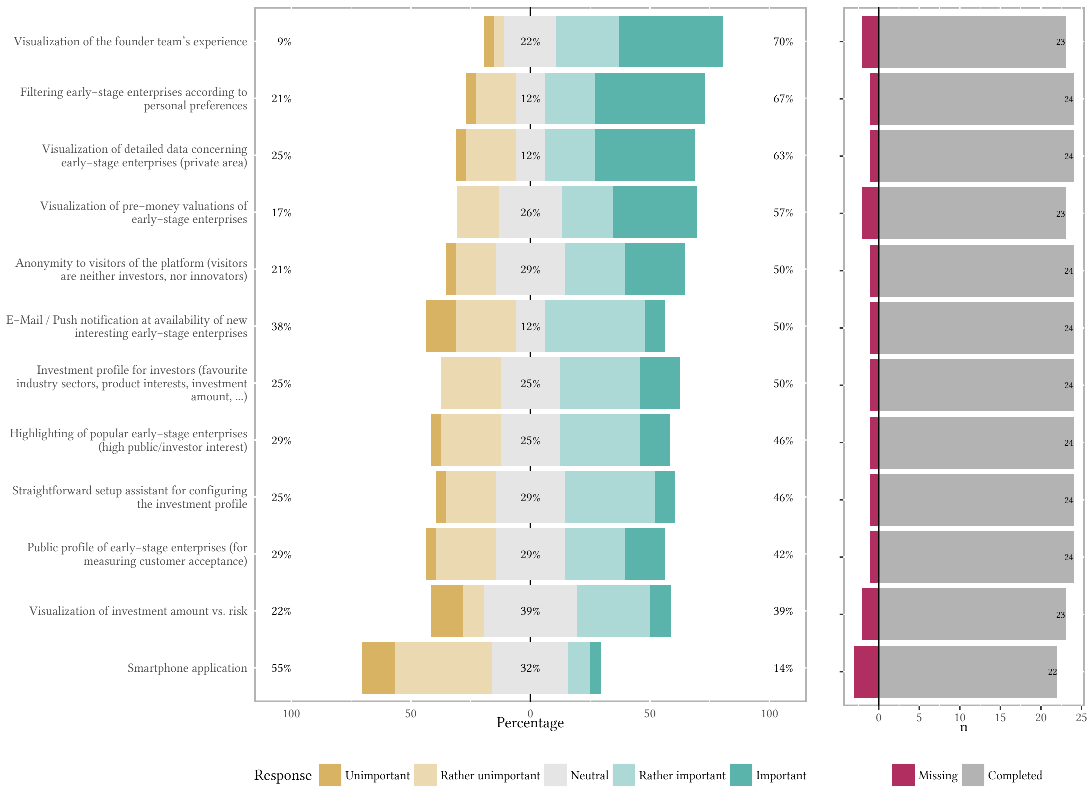

Figure 2.10: Question 6 – Plot (incl. histogram)

Reliability in terms of the internal consistency among participants' responses to the sub-questions is measured by utilizing *Cronbach's alpha* statistic, which indicates a std. alpha value of $\alpha = 0.82$. The reader is referred to appendix B.6 for a detailed analysis of reliability.

Statistical Tests are utilized for ascertaining whether the present sub-questions are normally distributed and conducting research on a possible applicability to the underlying (data)model of the recommender system. A test for normal distribution of participants' responses per sub-question is conducted utilizing the *Shapiro-Wilk Test* with the following hypotheses:

(i) H0: Participants' responses are normally distributed

(ii) H1: Participants' responses are not normally distributed

Table 2.26 shows that the ρ values calculated by the Shapiro-Wilk test are smaller than the significance level $\alpha = 0.05$ among *all* sub-questions. Therefore, the H0 hypothesis of each sub-question needs to be rejected, that is, no population of a corresponding sub-question is normally distributed.

Regarding research on the underlying (data)model of the recommender system, there are basically two questions to be analysed:

(i) Is there statistical significance about the fact that participants rated a certain sub-question either *Rather important* or *Important*?

    (a) Wilcoxon Signed Rank Test: Test whether the median m of a certain sub-question is greater than three.
    (b) H0: $m \leq 3$
    (c) H1: $m > 3$
    (d) Significance level: 97.5% ($\alpha = 0.025$)

(ii) Is there statistical significance about the fact that experienced- and inexperienced investors have a different opinion on a certain sub-question?

    (a) Wilcoxon Rank Sum Test: Test whether the location shift a between the distributions of experienced- and inexperienced investors differs significantly from 0.
        - H0: $a = 0$, H1: $a \neq 0$, that is, experienced investors rank the corresponding sub-questions *differently* than inexperienced investors.
        - H0: $a \geq 0$, H1: $a < 0$, that is, experienced investors rank the corresponding sub-questions *lower* than inexperienced investors.
        - H0: $a \leq 0$, H1: $a > 0$, that is, experienced investors rank the corresponding sub-questions *higher* than inexperienced investors.
    (b) Significance levels:
        - Two-tailed test: 95% ($\alpha = 0.05$)

- One-tailed tests: 97.5% ($\alpha = 0.025$)

As indicated in Table 2.26, the following sub-questions grouped by the corresponding tests are statistically significant—that is, the ρ values calculated by the tests are smaller than the significance level $\alpha = 0.05$ ($\alpha = 0.025$ respectively) among the corresponding sub-questions—and therefore, the H0 hypothesis needed to be rejected:

(i) Wilcoxon Signed Rank Test: *SQ1, SQ5, SQ7, SQ9*

(ii) Wilcoxon Rank Sum Test: *SQ4 ($a > 0$)*

Table 2.26: Question 6 – Statistical Tests

SQ	Sh.-W. T.		Wilcox. Signed Rank T.		Wilcox. Rank Sum T.			
	W	ρ	V	ρ	W	ρ $(a \neq 0)$	ρ $(a < 0)$	ρ $(a > 0)$
SQ1	0.83	0.001	187.5	0.005	39.5	0.863	0.432	0.602
SQ2	0.91	0.043	99	0.138	45.5	0.799	0.633	0.399
SQ3	0.87	0.006	126	0.032	61.5	0.105	0.956	0.053
SQ4	0.91	0.033	99.5	0.127	73	0.009	0.996	0.005
SQ5	0.81	0	195.5	0.002	44	0.897	0.585	0.449
SQ6	0.91	0.038	109.5	0.139	33.5	0.495	0.248	0.778
SQ7	0.85	0.002	133	0.003	38	0.963	0.482	0.555
SQ8	0.89	0.018	59	0.348	35	0.75	0.375	0.659
SQ9	0.82	0.001	154	0.001	31	0.488	0.244	0.784
SQ10	0.9	0.025	25.5	0.982	26	0.349	0.175	0.85
SQ11	0.87	0.006	123	0.398	60.5	0.116	0.951	0.058
SQ12	0.9	0.026	117	0.025	47.5	0.669	0.696	0.335

Evaluation In analogy to the previous passage, the findings of the analysis will be evaluated according to *reliability*- and *statistical tests* of the dataset.

As pointed out during analysis, reliability of the present question is stated as the std. alpha value $\alpha = 0.82$, which is considered *good*. In particular, this outcome means that the internal consistency among participants' responses to the present sub-question is *good*. Therefore, there are no objections—in terms of reliability—in utilizing the present dataset for further statistical analysis.

The fact that none of the sub-questions are normally distributed indicates that corresponding parametrized statistical tests can not be applied. Therefore, the decision on utilizing non-parametrized statistical tests for answering the following questions was correct.

The question whether there is statistical significance about the fact that participants rated a certain sub-question either *Rather important* or *Important* holds for the following sub-questions:

- SQ1 – Visualization of detailed data concerning early-stage enterprises (private area)
- SQ5 – Filtering early-stage enterprises according to personal preferences
- SQ7 – Visualization of pre-money valuations of early-stage enterprises
- SQ9 – Visualization of the founder team's experience

Therefore, characteristics of early-stage enterprises indicated by these sub-questions will be considered for the (data)model of the recommender system.

The question whether there is statistical significance about the fact that experienced- and inexperienced investors rated a certain sub-question differently—and in particular, whether experienced investors rated the corresponding sub-question lower/higher than their inexperienced counterparts—holds for the following sub-question:

- SQ4 – Straightforward setup assistant for configuring the investment profile *($a > 0$)*

Due to the fact that experienced investors ranked sub-question SQ4 higher than their inexperienced counterparts, the Wilcoxon Signed Rank Test shall be executed with the condition of only including experienced investors. However, the results of this test show a statistic of $V = 46$ paired with a p-value of $\rho = 0.026$, that is, there is no statistical significance about the fact that experienced investors rated sub-question SQ4 *Rather important* or *Important*. As a consequence, the present work will not consider SQ4 for the (data)model building phase of the recommender system, even though the ρ value lies at the very edge of indicating statistical significance.

Question 7: According to which criteria shall recommendations be generated?

The main objective of this question was to gain insights about the importance of certain criteria venture recommendations shall be based upon. The remainder of this question is stated as follows: The analysis references the Likert sub-question indexes instead of their corresponding descriptions (the reader is referred to the representation of index / sub-question mappings listed below). Finally, the analysed data is interpreted in the evaluation passage.

Subquestions

SQ1 Include early-stage enterprise recommendations that do not match your investor's profile

SQ2 Recommendations based on your former investment decisions

SQ3 Recommendations based on the investments or interests of other (certain) investors

SQ4 Recommendations based on an investor's profile

SQ5 Recommendations based on balancing your investment portfolio (risk vs. revenue)

SQ6 Recommendations based on the pre-money valuation of early-stage enterprises

Analysis In the course of this passage, the collected data of the present question is analysed according to the following categories: *descriptive statistics*, *reliability* and *statistical tests* of the dataset.

Descriptive Statistics quantitatively summarize and characterize the present data. Due to the fact that the dataset is based on an ordinal scale, it is not possible to calculate a degree of difference on a relative basis. However, ranking of the responses according to the question's underlying order is possible. Therefore, the *median* needs to be adduced as the *measure of central tendency*, rather than the *mean*. The reader is referred to Table 2.27 for summarized descriptive statistics of the dataset. Figure 2.11 visualizes an overall plot of participants' responses grouped by the answer set and ordered by the percentage of number of responses in the corresponding answer set in descending order. Additionally, the attached histogram visualizes missing- and completed answers per sub-question.

Table 2.27: Question 7 – Descriptive Statistics

SQ	Group	N	N (valid)	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
SQ1	Overall	25	22	2.773	1.066	1	2	2	4	5
	Yes	14	13	3	1.08	2	2	3	4	5
	No	7	6	2	0.632	1	2	2	2	3
SQ2	Overall	25	23	3.652	1.027	1	3	4	4	5
	Yes	14	13	3.462	1.266	1	3	4	4	5
	No	7	6	4	0.632	3	4	4	4	5
SQ3	Overall	25	23	3.087	1.125	1	2	3	4	5
	Yes	14	13	3.077	1.115	1	2	3	4	5
	No	7	6	2.833	1.169	1	2.25	3	3.75	4
SQ4	Overall	25	23	3.87	1.014	2	3	4	5	5
	Yes	14	13	3.692	1.032	2	3	4	4	5
	No	7	6	4	1.265	2	3.25	4.5	5	5
SQ5	Overall	25	22	2.864	1.246	1	2	3	3.75	5
	Yes	14	12	2.75	1.138	1	2	3	3	5
	No	7	6	3.167	1.722	1	2	3	4.75	5
SQ6	Overall	25	22	2.818	0.958	1	2	3	3.75	4
	Yes	14	12	2.667	0.888	1	2	3	3	4

To be continued…

...continued from previous page

SQ	Group	N	N (valid)	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
	No	7	6	2.833	1.169	1	2.25	3	3.75	4

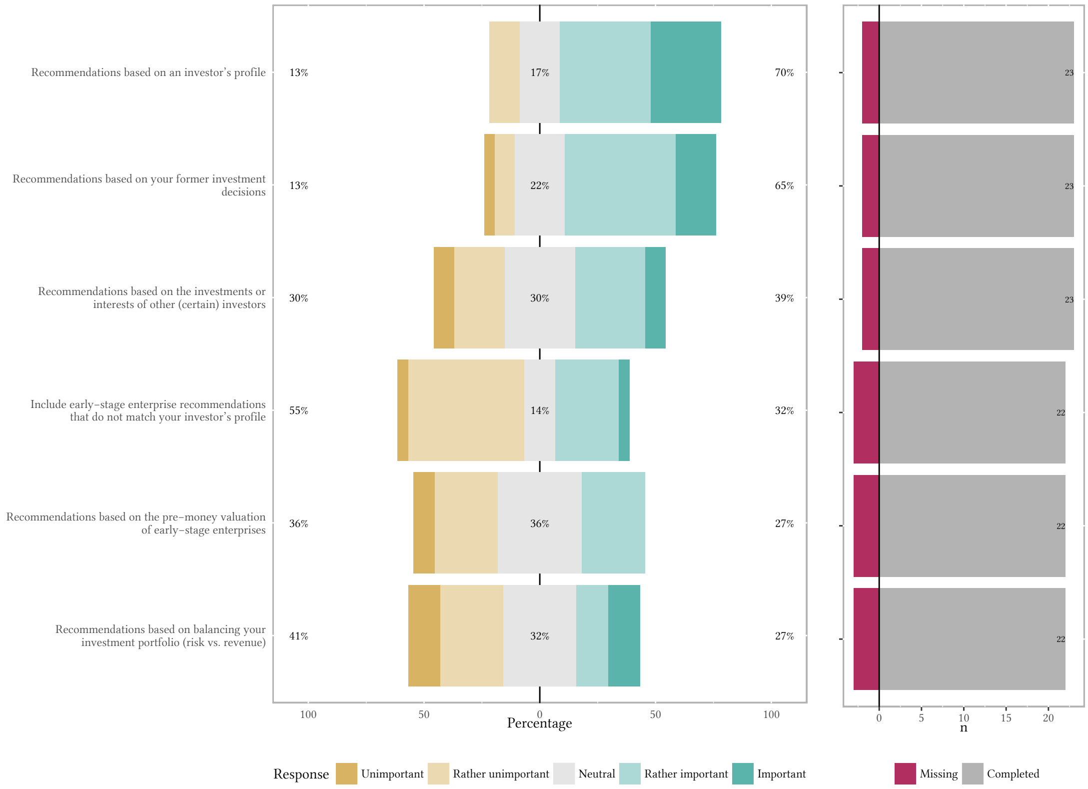

Figure 2.11: Question 7 – Plot (incl. histogram)

Reliability in terms of the internal consistency among participants' responses to the sub-questions is measured by utilizing *Cronbach's alpha* statistic, which indicates a std. alpha value of $\alpha = 0.51$. The reader is referred to appendix B.7 for a detailed analysis of reliability.

Statistical Tests are utilized for ascertaining whether the present sub-questions are normally distributed and conducting research on a possible applicability to the underlying (data)model of the recommender system. A test for normal distribution of participants' responses per sub-question is conducted utilizing the *Shapiro-Wilk Test* with the following hypotheses:

(i) H0: Participants' responses are normally distributed

(ii) H1: Participants' responses are not normally distributed

Table 2.28 shows that the ρ values calculated by the Shapiro-Wilk test are smaller than the significance level $\alpha = 0.05$ among all sub-questions but SQ3 and SQ5, that is, SQ3 and SQ5 are normally distributed (the H0 hypotheses of both sub-questions can not be rejected).

Regarding research on the underlying (data)model of the recommender system, there are basically two questions to be analysed:

(i) Is there statistical significance about the fact that participants rated a certain sub-question either *Rather important* or *Important*?

  (a) Wilcoxon Signed Rank Test: Test whether the median m of a certain sub-question is greater than three.

  (b) H0: $m \leq 3$

  (c) H1: $m > 3$

  (d) Significance level: 97.5% ($\alpha = 0.025$)

(ii) Is there statistical significance about the fact that experienced- and inexperienced investors have a different opinion on a certain sub-question?

  (a) Wilcoxon Rank Sum Test: Test whether the location shift a between the distributions of experienced- and inexperienced investors differs significantly from 0.

    - H0: $a = 0$, H1: $a \neq 0$, that is, experienced investors rank the corresponding sub-questions *differently* than inexperienced investors.
    - H0: $a \geq 0$, H1: $a < 0$, that is, experienced investors rank the corresponding sub-questions *lower* than inexperienced investors.
    - H0: $a \leq 0$, H1: $a > 0$, that is, experienced investors rank the corresponding sub-questions *higher* than inexperienced investors.

  (b) Significance levels:

    - Two-tailed test: 95% ($\alpha = 0.05$)
    - One-tailed tests: 97.5% ($\alpha = 0.025$)

As indicated in Table 2.28, the following sub-questions grouped by the corresponding tests are statistically significant—that is, the ρ values calculated by the tests are smaller than the significance level $\alpha = 0.05$ ($\alpha = 0.025$ respectively) among the corresponding sub-questions—and therefore, the H0 hypothesis needed to be rejected:

(i) Wilcoxon Signed Rank Test: *SQ2, SQ4*

(ii) Wilcoxon Rank Sum Test: *None*

Table 2.28: Question 7 – Statistical Tests

SQ	Sh.-W. T.		Wilcox. Signed Rank T.		Wilcox. Rank Sum T.			
	W	ρ	V	ρ	W	$\rho\ (a \neq 0)$	$\rho\ (a < 0)$	$\rho\ (a > 0)$
SQ1	0.83	0.002	72.5	0.845	59	0.062	0.975	0.031
SQ2	0.87	0.006	141	0.006	30	0.434	0.217	0.809
SQ3	0.92	0.077	74.5	0.372	43	0.75	0.659	0.375
SQ4	0.85	0.003	170.5	0.001	31.5	0.524	0.262	0.767
SQ5	0.91	0.057	52.5	0.681	31.5	0.7	0.35	0.685
SQ6	0.88	0.01	39	0.829	31.5	0.695	0.347	0.688

Evaluation In analogy to the previous passage, the findings of the analysis will be evaluated according to *reliability*- and *statistical tests* of the dataset.

As pointed out during analysis, reliability of the present question is stated as the std. alpha value $\alpha = 0.51$, which is considered *poor*. In particular, this outcome means that the internal consistency among participants' responses to the present sub-question lies at the edge of being *poor* or *unacceptable* respectively. One reason for this score may be seen in the considerably lower amount of sub-questions when compared to the other questions. Cronbach's Alpha statistic generally tends to be lower, if the number of items is low. Therefore, extending the number of items in the present Likert question might increase the score in future research. Another explanation of the low score may be seen in the fact that the sub-questions might be constructed too *broad* or *generic*. In this case, redefinition of the existing questions or adding additional questions might improve the score in future research. However, due to reasons of consistency in the present work, internal consistency of question seven is considered *accepted* under the condition of extending the size of the test sample (participants) [Cronbach, 1951, p. 323], and adding additional sub-questions in future research.

The fact that not the complete set of sub-questions of the present question is normally distributed, indicates that the corresponding parametrized statistical tests can not be applied. Therefore, the decision on utilizing non-parametrized statistical tests for answering the following questions was correct.

The question whether there is statistical significance about the fact that participants rated a certain sub-question either *Rather important* or *Important* holds for the following sub-questions:

- SQ2 – Recommendations based on your former investment decisions
- SQ4 – Recommendations based on an investor's profile

Therefore, these characteristics will be considered for the (data)model of the recommender system.

The question whether there is statistical significance about the fact that experienced- and inexperienced investors rated a certain sub-question differently—and in particular, whether experienced investors rated the corresponding sub-question lower/higher than their inexperienced counterparts—does not hold for any of the sub-questions. Thus, there is no indication that the median or distribution of values of experienced investors are statistically different from those of inexperienced investors. As a consequence, no information in this regard is considered for the (data)model of the recommender system.

2.3.3 Historical Data Analysis

As elaborated in subsection 2.2.4, the present topic addresses the analysis of the Crunchbase dataset in order to construct investment decision-making rules. However, in the course of the analysis and evaluation of the mentioned dataset, the author has come to the conclusion that the dataset does not contain the necessary data needed for the deduction of rules based on the constraints of early-stage enterprises. In particular, the ventures recorded in the snapshot can not be categorized as early-stage enterprises due to their considerably large historical track records and time of existence. Additionally, the dataset's model does not contain certain information needed for construction of investment decision-making rules especially applicable to the early-stage enterprise domain. As a consequence, the present work can not rely on the mentioned dataset and therefore, no decision rules are constructed and considered for the model building phase of the recommender system.

2.3.4 Discussion of Results

It was the main purpose of the present work to empirically evaluate investment decision-making criteria and venture valuation methods utilized by investors in the domain of early-stage enterprise investment. As results obtained by the qualitative expert interviews and the quantitative questionnaire suggest, the most important concern of investors when valuating early-stage enterprises, lies in the management team. In particular, the quantitative questionnaire's findings indicate that these teams need existing knowledge to implement the proposed product (idea) and the minimum amount of management team members needs to exceed one person.

A further important aspect among the valuation of early-stage enterprises arises from the characteristics of its target market or industry sector respectively. Thus, it is of great importance to investors that the targeted industry sector is not saturated and subsequently, the market entry of the early-stage enterprise's product idea is still possible. Additionally, there need to be indications that the target market is still in its growth phase and, consequently, shall not already be saturated. The last important characteristic of a beneficial market situation is indicated by low competition in the context of the early-stage enterprise's product (idea).

The qualitative expert interviews and the quantitative questionnaire further indicate that an early-stage enterprise's product (idea) itself is another major aspect affecting the valuation by investors. Among the most important characteristics in this regard resides the maturity level of the product idea—in fact, the product idea shall already be elaborated and contain an implemented prototype—and the acceptance of the product idea by potential customers (as may be indicated by market research).

Results obtained by the qualitative expert interviews further indicate that the utilization of classical venture valuation methods, that is, methods that base the foundation of the valuation process on an enterprise's historic business activities, are not applicable to the valuation of early-stage enterprises. However, investors still tend to use these methods in an abbreviated form—abbreviation by exploiting experience and gut feeling—due to the belief that there are no methods producing more objective- and meaningful valuations. As a consequence, the quantitative questionnaire researched valuation methods especially applicable to the valuation of early-stage enterprises. Despite the outcome of the qualitative expert interviews, its findings indicate that the most utilized ones of these methods are the scorecard-, venture capital-, and risk-factor summation methods. Interestingly, although similar in calculation, the berkus method is completely unknown to most participants. Due to the aforementioned facts and the support by the literature, the utilization of the scorecard- together with the berkus method as basis for the (data)model building phase of the recommendation system, is highly advisable.

Finally, participants of the qualitative expert interviews had rather concrete ideas about the potential functionality of a recommender system in the domain of early-stage enterprise investment, introducing added value to investors. The quantitative questionnaire was utilized to distinguish- and elaborate on the importance of certain functions. As its results indicate, the *filtering of early-stage enterprises according to an investor's personal preferences*, *visualization of early-stage enterprises' pre-money valuations*, the general *illustration of early-stage enterprises' detailed data in a restricted (non-public) area* and the *representation of a founder team's experience* may be stated as the most important findings. However, the results further suggest that the *recommendation of early-stage enterprises from investor to investor* and *recommendations based on an investor's former investment decisions* are also considerably important to the participants of the qualitative expert interviews and the quantitative questionnaire respectively.

2.4 Answers to the Research Questions

The present work's research questions (the reader is referred to subsection 2.2.1 of the methodology) are answered on the basis of subsection 2.3.4 in the following passages grouped by research question. Furthermore, implications on the recommendation system are conducted in the course of answering the third research question.

How can investment decision-making requirements and behaviours of investors be quantified for being used in a recommender system?

This question primarily targets the appropriateness of scientific instruments utilized to quantify investors' decision-making criteria with the aim of use in a recommendation system. Additionally, this question contains two sub-questions asking about the elaborated characteristics of investors and early-stage enterprises. As described in great detail in the methodology section, a combined approach of two scientific methods may be considered reasonable for this task. The former consists of an expert interview with the aim of elaborating general knowledge in the domain of early-stage enterprise investment. Subsequently, the purpose of the latter scientific instrument—the quantitative questionnaire—is stated as quantifying certain parts of the previously acquired knowledge by participating investors and experts in the field of early-stage enterprise investment. Finally, the reader is referred to the previous subsection 2.3.4 for summarized answers to the current research question's sub-questions.

Which venture valuation methods best model the characteristics of early-stage enterprises?

The literature and both findings of the qualitative expert interviews and quantitative questionnaire respectively suggest that the *scorecard- and berkus methods* best fit the requirements to valuation methods in the context of early-stage enterprise valuation. This decision is based on the following facts:

- Both the scorecard- and the berkus method are future-minded and therefore do not base their valuations on historic business activities.
- No other valuation methods need to be conducted prior to- or in the course of the selected methods, indicating an advantage to other valuation methods in terms of independence.
- The empirical research's participants' responds tend towards the beneficial use of the scorecard- and berkus methods (the reader is referred to subsections 2.3.1 and 2.3.2 for a detailed elaboration).

How do the identified investment decision-making characteristics and venture valuation methods affect the model of a recommender system in the domain of early-stage enterprises?

Based on the previous question and discussion in the previous subsection, the utilization of the scorecard- and berkus methods—and subsequently their underlying model—are chosen as primary part of the recommendation system's model, including all the necessary entities needed in the mentioned valuation methods. As a consequence, the recommendation system shall incorporate the following functions in order to generate added value to its users:

- Display of valuations for early-stage enterprises.
- Illustration of detailed data about early-stage enterprises and their corresponding (management) team.
- Implementation of an investor's profile that allows for personalization of early-stage enterprise recommendations and filtering of such enterprises according to personal preferences.
- Incorporation of a recommendation approach that utilizes the quality of the management team, product- & public interest and industry/market sector, for it is these aspects that are regarded considerably important decision-making criteria upon investors.
- Trust between investors affects an investor's investment behaviour considerably, resulting in the fact that it is highly advisable for a recommendation system to model investors' trust among each other and utilize these implications for the recommendation of enterprises.

Conclusion

The purpose of the specialization topic *Investment Decision-making & Venture Valuation* was to gain qualitative insights on investment decision-making criteria and venture valuation methods utilized by investors and quantitatively research, which of these criteria and methods may be included in the model-building phase of a recommender system in the domain of early-stage enterprise investment. As a consequence of the present research, these systems are enabled to successfully address the problem of information overload in the domain of early-stage enterprise investment by computational calculation of enterprise recommendations and therefore, these systems gain the ability to actively support and improve investors' investment decision-making processes.

The scientific instruments utilized to research the early-stage enterprise investment domain were stated as qualitative expert interviews, followed by a quantitative questionnaire. Whereas the goal of the former instrument was to gain a general insight in the corresponding field of research, the latter was utilized to quantitatively elaborate on the qualitatively researched data. The findings of the present research are quite convincing and thus, the following conclusions can be summarized: The most important characteristics investors base their investment decisions on, are stated as the quality, size and composition of the management team, product- & public interest- and the industry/market sector of an early-stage enterprise. Furthermore, the venture valuation methods most utilized by investors, most meaningful in terms of valuation quality in the context of early-stage enterprises and most beneficial when utilized in a recommendation system, are stated as the scorecard- and berkus methods. Finally, investors' requirements among the functionality of a recommender system in the domain of early-stage enterprise investment may be concluded as the construction of an investor profile that allows for personal visualization- and filtering of early-stage enterprises, trust relationships among investors and the illustration- and calculation of early-stage enterprises' pre-money valuations.

This thesis's specialization topic is a modest contribution to the ongoing discussion of objectively quantifiable success factors of early-stage enterprises and especially researches requirements of a recommender system's model of the early-stage enterprise investment domain. The present work shows that the most important characteristics of investors' investment decision-making criteria basically comply to the ones discussed in the economic literature. Nevertheless, new insights about investors' use of venture valuation methods in the domain of early-stage enterprise investment was researched and therefore, this work actively contributes to the economical field of research. Furthermore, scientific research in the domain of recommender systems benefits from the researched requirements to a recommendation system's model in the domain of early-stage enterprise investment. Finally, the proposed research can be rapidly used in practice or further investigated in the course of future research. However, to the author's best knowledge, very few publications are available in the literature that discuss the problem of early-stage enterprise investment in the domain of computational recommendation systems. As a consequence, certain limitations to the present research arise that may be based on, but are not limited to, the fact of uncertainty of the present research due to considerably little research in the mentioned field of science.

Limitations to the present work may be seen in the following aspects: Participants of the qualitative- and quantitative questionnaire only originate from two locations, that is, Austria and Germany. However, in order for broader scientific results in terms of globally utilized investment decision-making criteria and venture valuation methods, a considerably higher amount of participants whose origins are distributed around the world may be needed in the course of equivalent scientific instruments. Furthermore, the researched scientific results may benefit from the outcomes of a other scientific instruments.

Future research may address the mentioned limitations of the present work. In particular, the comparison of the researched data to the findings of other scientific research instruments is of great interest. One specific scientific instrument may be seen in the deduction of general investment rules based on the analysis of a dataset on historic investment deals, which, subsequently, proposes the opportunity of elaborating on the appropriateness of the present work's utilized scientific instruments. However, the most important outcome of the present work that may also be seen as the most important opportunity for further research, is stated as the construction of a recommender system based on the requirements formulated by the present specialization topic. In fact, it is precisely this very opportunity that is researched in chapter 3 of this thesis.

CHAPTER 3

Recommender Systems for Early-Stage Enterprise Investment

3.1 Background

The very purpose of the current section 3.1 is defined as the elaboration of basic concepts of the *recommender systems* area of research. Furthermore, challenges and current research trends in the domain of computational recommendation systems are elaborated. Finally, a terminology of the basic concepts is being established by the definition of mathematical conventions and symbols, which is further utilized throughout the present work.

3.1.1 Recommender Systems Classification

The purpose of computational recommendation systems, which are also referred to as *recommender systems*, is the suggestion of *items* (certain topics of interest such as music, movies or news) the user might prefer over other items [Ricci et al., 2010]. These systems are usually implemented as algorithms in software. In order to improve accuracy of decision-making processes using recommendation algorithms, *user data* such as gender, age or interests is typically utilized and provided *directly* by the user or *indirectly* by analysis of user behaviour. In general, recommender systems help users evaluate *favourable* items in a large set of objects. In addition to adapting to the user's needs and consequently the enhancement of user satisfaction while interacting with the software, companies gain certain improvements such as the increase of sold items, user fidelity and -satisfaction, through the application of recommendation techniques [Ricci et al., 2010]. Due to its nature, the field of application concerning recommender systems is widespread, but usually addresses *Digital Media*, *E-Commerce* and *online services* such as travelling recommendations. Furthermore, the highly diverse field of application scenarios mostly relies on custom approaches to designing recommendation algorithms, leading to an even more complicated, extensively increasing field of study. As a consequence, recommender systems are classified into mainly three different categories, that is, *collaborative filtering*, *content-based recommendation* and *knowledge-based recommendation* [Jannach et al., 2010].

Due to the aspects of the present work, the previously mentioned recommendation categories as well as the specialization research areas of *social-* and *hybrid* recommendation systems are being investigated in the following subsections.

Collaborative Filtering Recommender Systems

The first of the three classification categories—*collaborative filtering*, which is also referred to as *collaborative recommendation*—exploits the overlapping interests between users, that is, the recommendation of items based on their shared set of interest [Jannach et al., 2010]. As an example, the purchasing history of user X and user Y at an online music store may be taken into account. It is assumed that the purchasing history of user X and Y is overlapping, implying a highly similar taste in music. If user X purchased a new song, a recommendation algorithm based on a collaborative filtering technique is very likely to propose the same song to user Y. In general, the main obstacle of this approach may be seen in the filtering of redundant items. Furthermore, *collaborative recommendation* addresses questions such as *How is similarity measured?*, *What about the recommendation of items that have never been sold yet?* and *What if the amount of ratings on an item is very low?* Due to its nature, the *Collaborative filtering* approach does not require any information about the *characteristics* or *attributes* of the item itself [Jannach et al., 2010]. This fact may be regarded a disadvantage, because recommendations might not only be based on overlapping user interests, but also on the content of items.

According to Aggarwal [2016, p. 29], neighbourhood-based collaborative filtering algorithms—which are also referred to as memory-based algorithms—were among the earliest algorithms developed in the context of collaborative filtering recommenders. These algorithms are based on the fact that similar users apply similar patterns of rating behaviour and, therefore, similar items receive similar ratings. The literature on collaborative filtering techniques mainly distinguishes these concepts into *User-based Neighbourhood Collaborative Filtering* and *Item-based Neighbourhood Collaborative Filtering*.

User-based Neighbourhood Collaborative Filtering While its calculation of recommendations is based on ratings provided by peer users similar to a target user, Jannach et al. [2010, p. 13] state that the main idea behind the user-based collaborative filtering approach is specified as follows: Given a ratings database and a target user, identify a set of peer users whose historic interests are similar to those of the target user and finally, predict items to the target user based on the identified neighbourhood users. Subsequently, the predicted score for the target user is computed by the peer users' item ratings.

Item-based Neighbourhood Collaborative Filtering In contrast to the user-based approach, item-based collaborative filtering calculates predictions utilizing the similarity between items instead of users [Jannach et al., 2010, p. 18]. In order to predict the rating of a target user for a target item, the target user's ratings for a set of peer items similar to the selected item are considered. Finally, an item-based algorithm calculates a weighted average of all peer item ratings and predicts a rating for the target item to the target user.

Content-based Recommender Systems

Content-based recommendation—the second class of recommendation algorithms—mainly relies on information retrieved from the content of items and therefore, future recommendations are only based on content similarity between the *selected*- and the *investigated* item. Taking again the previous example of the shared purchasing history of user X's and Y's music into account, a content-based recommendation algorithm would recommend songs based on genre, band, year et cetera. The dependency on the purchasing history between user X and Y is—unlike the *collaborative filtering approach*—not taken into account. Additionally, information about the user's purchasing history and profile may automatically be retrieved (for instance via the purchasing behaviour) or manually set (such as preferences, interests and personal data about the user). According to Jannach et al. [2010], content-based recommendation algorithms have the advantages of direct recommendation once item information is available and the unnecessity of large user groups for an increase of recommendation accuracy, compared to other recommendation approaches. On the other hand, information on items mostly has to be provided manually, which may be expensive and prone to errors.

More formally, content-based recommender systems calculate (and recommend) a set of items that are most similar to a target user's already known items in terms of their *content*. [Jannach et al., 2010, p. 51] regard the following information the only necessity to this process:

(i) A description of the item characteristics

(ii) A user profile that describes (historic) interests of a user

However, both collaborative- and content-based recommendation techniques have the prerequisite of a purchasing history in common. Naturally, there are scenarios of unavailability of such purchasing histories, making collaborative- and content-based recommendation algorithms inapplicable.

Knowledge-based Recommender Systems

The present category of recommendation algorithms is referred to as *knowledge-based recommendation*, which—in contrast to the previously introduced recommendation approaches—mainly concentrates on mostly manually provided information on both the user and the object of interest. Therefore, this type of recommendation systems is not relying on the prevalence of a user's purchasing history [Jannach et al., 2010]. A car market place may be considered as an example. The average user buys a car just every couple of years, making it impossible for a recommendation algorithm to create a user profile—this user behaviour is also referred to as *one-time buyer*. In order to address this problem, knowledge-based recommendation algorithms consider characteristics of cars such as *age*, *driven distance*, *performance* or *brand* in combination with certain preferred features selected by the user (for instance via a virtual user interface).

Furthermore, user preferences may be weighted according to the relative importance to the user. Therefore, a so called *constraint-based recommender*—one of many different recommendation algorithms in the domain of knowledge-based recommender systems—is applied to match an aggregate of cars to the preferences of a user, resulting in a filtered set of cars most probably liked by the user. Due to this fact, it may be implied that the success of a knowledge-based recommender system relies on the interaction with the user. As a consequence, more elaborate approaches tend to implement an *interaction style* based on human conversation [Jannach et al., 2010].

Social Recommender Systems

Traditional recommender systems commonly ignore social connections between users [Massa and Avesani, 2004, p. 493]. In contrast, social recommender systems are based on social network structures such as trust and distrust. Recent research has shown that merging social network structures and recommender systems may improve the accuracy of recommendations and the user's experience [Aggarwal, 2016, p. 23]. Users who are socially connected are more likely to share the same- or similar interests. Subsequently, users may easily be influenced by *trusted* users, that is, there exists a high likelihood that a trusted person's recommendations are trusted as well [Victor et al., 2011, p. 49]. As a result, social trust relationships are highly correlated with similarity, that is, users usually have more trust in similar users. However, it is important to inform about the *asymmetry* of trust, leading to the fact that trust may be modelled as directed graph. An example may be seen in users that directly specify their trust or distrust relationships to other users. This obtained trust information is considered highly beneficial in the context of a user-based neighbourhood collaborative filtering algorithm, which computes more accurate recommendations by the sole utilization of trusted peer users [Victor et al., 2011, p. 52].

Hybrid Recommender Systems

Whereas the previously introduced recommendation techniques possess various advantages and disadvantages, hybrid recommenders leverage and combine multiple recommendation techniques in order to maximize recommendation performance in terms of quality (a user's utility) and outweigh the corresponding disadvantages (such as the coldstart / ramp-up problem) introduced by each of the utilized recommenders when applied separately. In particular, Burke states:

> “ …Hybrid recommender systems combine two or more recommendation techniques to gain better performance with fewer of the drawbacks of any individual one. Most commonly, collaborative filtering is combined with some other technique in an attempt to avoid the ramp-up problem. …
>
> *Burke [2002, p. 339]* ”

According to Jannach et al. [2010, pp. 128–142], hybrid recommendation systems are commonly divided into *monolithic*-, *parallelized* and *pipelined* hybridization designs. While a monolithic hybridization design comprises a single recommender that integrates various recommendation algorithms by preprocessing- and combining different sources of knowledge, a parallelized hybridization design consists of multiple recommenders and a component that merges their results. In analogy to the latter, pipelined hybridization designs consist of multiple recommenders that are consecutively applied on a list of items. Independently, the introduced hybridization designs are further distinguished as follows: [Jannach et al., 2010, pp. 128–142; Burke, 2002, p. 340]

(i) Monolithic hybridization design
- Feature combination
- Feature augmentation

(ii) Parallelized hybridization design
- Mixed
- Weighted
- Switching

(iii) Pipelined hybridization design
- Cascade
- Meta-level

In particular, *cascade hybrids* are considerably important in the course of the present work and are therefore described as follows: As stated earlier, being a member of the category of pipelined hybridization designs, the cascade hybrid consists of multiple recommenders that are consecutively applied on a list of items. This procedure sequentially refines the ranking of the list's items after each recommendation algorithm's application. However, only the initially applied recommender may alter the items included in the list of items, that is, the consecutively applied recommenders are prohibited from removing or adding items to the list. Ultimately, the last iteration calculates the final ranking of the item list.

3.1.2 Challenges and Current Trends in Research

Concluding major classification types of recommendation algorithms, a large field of study may be outlined. Be it *collaborative filtering*, *content-* or *knowledge-based recommendation*, *social-* or *hybrid recommender systems*: each approach has certain advantages and disadvantages depending on the goal about be achieved. However, the downside of the nearly endless range of applicable scenarios in the context of computational recommendation systems is the rise of a very complex problem domain.

The biggest problem of recommendation algorithms based on a ratings structure, arises from the estimation of ratings for items unknown to the user [G. Adomavicius and Tuzhilin, 2005]. In a more formal way, the goal of a recommendation algorithm is the maximization of a user's utility, that is, only items unknown to the user and exposing the highest probability of user satisfaction are recommended. In order to address this problem, algorithms usually rely on ratings for other items given by the same user. This fact also indicates the requirement of an initial subset of user ratings, before recommendations based on a ratings structure can be given. This scenario is also referred to as the *cold start* problem [Schein et al., 2002]. After gaining an initial set of ratings, a user's utility is usually extrapolated utilizing methods of various domains such as machine learning, approximation theory or heuristics [G. Adomavicius and Tuzhilin, 2005]. Another problem deriving from a considerably small amount of quantified input data needed for extrapolation, may be seen in the user's trust into the Recommendation System [Ricci et al., 2010]. Wrong recommendations directly affect the trust a user has into the system, possibly resulting in the avoidance of the platform. Due to the high complexity of the mentioned problem domain, recommender systems have become an important research area, having roots in various fields of study.

According to G. Adomavicius and Tuzhilin [2005], recommender systems have become an independent research area during the mid-1990s with roots in the fields of cognitive science, approximation theory, information retrieval, forecasting theory, management science and marketing [G. Adomavicius and Tuzhilin, 2005]. Nowadays, conferences and special interest groups such as *ACM Recommender Systems (RecSys)* and *User Modeling, Adaptation and Personalization (UMAP)* were founded to thrive research in the area of recommendation algorithms [Ricci et al., 2010]. Considering the early age of start of research, *Recommender Systems* is a very young field of study that combines logics, human computer interaction (HCI), data mining and information retrieval. Due to its multidisciplinary nature, many challenges such as performance of algorithms, privacy & security issues and diversity of recommendations arise. Current emerging research topics can be seen in multidisciplinary areas, for instance, new visualization techniques, recommendations based on trust, personalization & search involving whole communities, social tagging systems (STS), recommendations based on different coherences and addressing security issues [Ricci et al., 2010].

3.1.3 Mathematical Conventions and Symbols

The first step of defining solutions (mathematical calculations) to the problem domain of the recommendation system lies in the definition of mathematical conventions and symbols. This subsection covers the basic symbols utilized throughout the present work. More advanced topics are elaborated in the corresponding sections 3.2 and 3.3.

In order to conform to the common recommender systems terminology, the present work will address *investors* as *users* and *ventures* as *items*. Let $\mathcal{U} = \{u_1, \ldots, u_{|\mathcal{U}|}\}$ be defined as the set of users and $\mathcal{I} = \{i_1, \ldots, i_{|\mathcal{I}|}\}$ as the set of items held by the platform. Without loss of generality, it shall be defined that the implementation of the present recommendation system is only permitted to recommend items *not yet known* to a certain user.

Similarity

In the concept of recommender systems, *similarity* of entities (user or item) plays an important role. Recommendations are created based on the assumption that similar users like similar items. The degree of distinction between the target- and an investigated (peer) *entity*—which is also referred to as *similarity*—, is dependent on the attributes of the entity (such as users or items) itself, that is, the *distinguishing features*, and the applied similarity measure [Huang, 2008, p. 51]. The result of a similarity measure is commonly represented as a numeric value, whereas larger values imply higher similarity and small values low similarity analogously.

As pointed out earlier, a similarity measure's main purpose is to find the degree of distinction between two entities. However, similarity measures are not universally usable. On the contrary, the selection of a similarity measure highly depends on the underlying type of dataset. Therefore, the following subsections elaborate on similarity measures utilized in the course of the present work.

Jaccard Similarity Coefficient Jaccard [1912, p. 39] defines the so called *coefficient of community* as the size of the intersection of two target sets A and B divided by the size of their union, more formally:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} \,\Big|\, 0 \leq J(A,B) \leq 1 \tag{3.1}$$

$J(A,B)$ is a function $J : A, B \rightarrow \{x \in \mathbb{R}_{\geq 0} : x \leq 1\}$, whereas an output of 1 signals that two sets are similar and —analogously —0 specifies that two sets are dissimilar to each other.

The Cosine Similarity Coefficient is commonly utilized in the fields of information retrieval and text mining with the aim of comparing text documents represented as vectors of terms. The metric measures the similarity between two non-zero n-dimensional vectors based on the angle between them. The similarity between two items a and b—views of the corresponding vectors a and b—is formally defined as follows:

$$\cos(a,b) = \frac{\langle a,b \rangle}{|a| * |b|} \tag{3.2}$$

In the Euclidean space $\mathbb{R}^n$, the inner product $\langle a,b \rangle$ is given by the dot product. $\langle a,b \rangle$ is defined as $\sum_{i=1}^{n} a_i b_i = a_1 b_1 + a_2 b_2 + \cdots + a_n b_n$, where $|a|$ is stated as the Euclidean length of the vector, which is defined as the square root of the dot product of the vector with itself [Jannach et al., 2010, p. 19]. Furthermore, $\cos(a,b)$ is a function $\cos : a, b \rightarrow \{x \in \mathbb{R}_{\geq 0} : x \leq 1\}$, whereas —assuming the constraint of positive vector entries—1 states that the target- and investigated entities are *equal* and 0 expresses that both entities entirely *differ* from each other.

However, the cosine similarity coefficient has one major disadvantage, that is, the difference in rating scales between various users are not taken into account. As a consequence, the *adjusted cosine similarity* measure addresses this disadvantage by subtracting the corresponding mean from each co-rated pair [Sarwar et al., 2001, p. 288]. The output of the adjusted cosine similarity measure ranges in the interval of -1 to 1 in $\mathbb{R}$.

The Kendall Tau Distance $\mathcal{K}(\tau_1, \tau_2)$ is stated as commonly utilized *distance measure* for two total orders τ_1 and τ_2. This measure counts the number of *disagreements* between τ_1 and

τ_2 regarding pairs of candidates—which is also referred to as *discordant pairs* [F. Brandenburg, 2011, p. 3]. More formally, let the Kendall tau distance be defined as

$$\mathcal{K}(\tau_1, \tau_2) = \frac{\sum\limits_{\{a,b\} \in P} \bar{\mathcal{K}}_{a,b}(\tau_1, \tau_2)}{n \cdot (n-1)/2} \tag{3.3}$$

where P is a set of unordered pairs of distinct elements in τ_1 and τ_2, $\bar{\mathcal{K}}_{a,b}(\tau_1, \tau_2) = 0$ if a and b are in the same order in τ_1 and τ_2 or $\bar{\mathcal{K}}_{a,b}(\tau_1, \tau_2) = 1$ if a and b are in the reverse order in τ_1 and τ_2 [Fagin, Kumar, and Sivakumar, 2003, p. 140]. Subsequently, $\mathcal{K}(\tau_1, \tau_2)$ equals to 0 if the two lists are exactly the same. Analogously, if one list is the reverse of the other, that is, both lists are of entirely opposite order, $\mathcal{K}(\tau_1, \tau_2)$ equals to $n(n-1)/2$ (where n is stated as the number of elements in the list).

Neighbourhood Formation

Another major design choice in the context of similarity measures that has a considerably large impact on recommendation quality and computational performance, lies in the *selection of the entity's neighbourhood*, that is, the (sub-)set of entities that are considered similar to a target entity. However, Jannach et al. [2010, pp. 17–18] argue that including the whole neighbourhood of entities affects the precision of recommendations due to the consideration of *false positives*, in other words, entities that are not significantly similar to the selected entity. Additionally, considering the whole entity neighbourhood could drastically increase calculation time (depending on the size of the neighbourhood).

The commonly accepted technique addressing the problems arising from a large neighbourhood lies in the reduction of its size either by definition of a *minimum similarity threshold* or by declaration of a maximum neighbourhood size k, that is, only including the k *nearest* neighbours in terms of similarity [Jannach et al., 2010, pp. 17–18]. However, limiting the size of the entity's neighbourhood introduces negative side effects such as finding the *fitting* value for k or the reduction of prediction coverage due to considerably high similarity thresholds. Therefore, Herlocker, Konstan, and Riedl [2002] conducted various experiments concerning the analysis of different weighting schemes and neighbourhood sizes. Based on the *MovieLens dataset*[1], Herlocker, Konstan, and Riedl argue that the entity's neighbourhood shall contain 20 to 50 entities in order to fit various real-world applications.

[1] MovieLens dataset: https://grouplens.org/datasets/movielens/

3.2 Methodology for Modelling Requirements

In the the course of the *methodology*, the reader is informed about the scientific approach utilized in the course of the present chapter, which is needed in order to gain knowledge for answering the research questions. The remainder of this section is organized as follows: Subsection 3.2.1 outlines the problem definition including the associated research questions, whereas subsections 3.2.2 to 3.2.6 describe different types of recommenders that are based on the research of the previous chapter 2 and are about to be modelled throughout the upcoming results section. Finally, subsection 3.2.7 introduces the reader to the constraints of the recommendation system's software prototype.

3.2.1 Problem Definition & Research Questions

The research conducted in the present chapter is stated as the mathematical formulation of a recommendation system in the domain of early-stage enterprise investment, which is based on the qualitative- and quantitative research undertaken in the previous chapter 2. In addition, the modelled recommendation system is being implemented as a software prototype. Finally, the following research questions will be answered:

(i) Which recommendation algorithms and -techniques shall be considered in a computational recommendation system in the domain of early-stage enterprise investment, in order to guarantee highly personalized recommendations for investors?

(ii) How can the *cold start problem* in the context of computational recommendation systems in the domain of early-stage enterprise investment, be addressed?

(iii) Which constraints does a software prototype of the computational recommendation system need to fulfil, in order to guarantee technical- and algorithmic feasibility?

With the aim of scientifically answering the mentioned research questions, the methodological approach addresses the *transition* from the venture valuation- and early-stage enterprise investment research conducted in the previous chapter, to potentially fitting recommendation approaches (the reader is referred to Figure 3.1 for a detailed overview of the transitioning process). Therefore, the following subsections represent different types of recommenders, elaborate on the findings researched in chapter 2 and discuss a possible conformity to certain recommendation algorithms. The mathematical modelling of these systems is conducted throughout section 3.3. Finally, section 3.4 discusses the results and provides answers to the research questions.

3.2.2 Collaborative Filtering

A very interesting and controversial finding of the present work's previous chapter may be seen in the fact that users incorporate the opinions of other users into their investment decision-making processes. In particular, the term *opinion* may be interpreted as a user's interaction upon items and expressed as *ratings* of various types (the reader is referred to the model

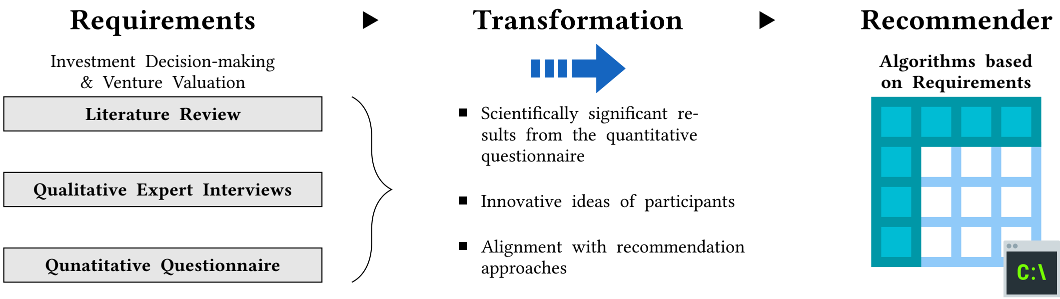

Figure 3.1: Transition process from venture valuation- and investment decision-making requirements to recommendation algorithms.

subsection 3.3.1 for a detailed introduction to the present work's implementation of rating structures). This behaviour considerably relates to a commonly utilized recommendation approach—*Collaborative Filtering*.

Collaborative filtering techniques exploit the overlapping interests between users, that is, the recommendation of items based on their shared set of interests. As mentioned in the background section 3.1, these techniques base their recommendations on the fact that similar users apply a similar rating behaviour on items. Jannach et al. [2010, p. 3] state that due to its independence from an item's attributes, collaborative filtering approaches may be applied in situations where analysis of the content is difficult. In the context of the present present work, this fact is regarded an advantage, for it is the users' interests that might not entirely be based on the similarity of items' contents.

Due to the aforementioned aspects, the authors conclude that collaborative filtering techniques are beneficial for generating recommendations that improve user satisfaction in the context of early-stage enterprise investment. The reader is referred to subsection 3.3.2 for a detailed description of the present work's implementation of the user-based- and item-based neighbourhood collaborative filtering approaches.

3.2.3 Content-Based Recommendation

One crucial finding of the present work's previous chapter may be seen in the fact that a user's personal interests are considered highly important for the utilization in the domain of early-stage enterprise investment. A recommendation approach that highly correlates to this finding is defined as *Content-based Recommandation*, which utilizes the comparison of content among a user's historically interested items and new ones, that is, unknown items.

In contrast to the collaborative filtering approach, a content-based recommender has the advantage of not being reliant upon users' ratings data. As mentioned in the background section 3.1, a content-based recommendation system generates predictions based on an item's attributes combined with the target user's interests. The previous chapter's findings show that a user's most important item attributes are defined as follows (the reader is referred to the model subsection 3.3.1 for a detailed introduction to the present work's implementation of the recommender's domain model):

- Product Interest
- Market Sector
- Life Cycle

In context to the previous chapter's research, the authors want to highlight the importance of content-based recommenders in the domain of early-stage enterprise investment. This technique provides solutions to problems such as *sparse ratings data* that especially apply to the domain of early-stage enterprise investment. Due to these aspects and the support by the scientific literature, the authors decide on implementing a content-based recommender in the course of the present work. The reader is referred to subsection 3.3.3 for a detailed representation of the content-based recommender's concept, model and mathematical foundations.

3.2.4 Knowledge-Based Recommendation

One of the main findings of the present work's previous chapter indicates that sorting/filtering of early-stage enterprises according to a user's personal preferences is considered highly important for the use in a recommender system. As discussed in the background subsection 3.1.1, knowledge-based recommender systems mainly base their recommendation algorithms on manually provided information on attributes of an item and the target user. Subsequently, these systems have the advantage of not being reliant upon a user's purchasing history and item ratings by other users. Furthermore, knowledge-based recommendation systems are commonly utilized if other recommendation techniques (such as collaborative filtering) are inapplicable. This is especially the case for considerably sparse ratings sets, as in the domain of early-stage enterprise investment.

In contrast to domains more accustomed to the use of recommender systems that are commonly based on large-scale ratings sets—such as digital media or e-commerce—the authors of the present chapter presume that ratings sets in the domain of early-stage enterprise investment are considerably sparse. This assertion is based on the results of the qualitative research conducted in chapter 2 of the present work. In the course of expert interviews it has been shown that especially business angels hold/invest only in a handful of early-stage enterprises. This statement is also supported by the fact that the invested money per item is considerably higher when compared to other domains, leading to the phenomena of *one-time buyers*. Furthermore, knowledge-based recommender systems do not face the *cold start* problem, that is, a recommendation of early-stage enterprises may even be conducted in the early times of platform existence, due to the fact that these systems do not rely upon ratings of other users.

Due to the aforementioned reasons, the authors conclude that the expression of a user's personal preference through the utilization of a user's choices upon an early-stage enterprise's attributes, is seen as highly beneficial to the user's satisfaction. In particular, as the previous chapter of the present work has shown, these choices are based on an item's attributes most important to the user and are comprised of- but not limited to the following listing:

- Investment- and share ranges of items
- Venture valuations
- Date of creation
- Market sector
- Interest in an item based on *tags* describing an item's products
- Interest of potential future customers in the item
- Team
- Life cycle stage

Based on the introduced facts, the authors conclude that the present work highly benefits from knowledge-based recommendation techniques in terms of recommendation quality and user satisfaction. Subsequently, the authors decide that the present work shall implement a knowledge-based recommendation algorithm. The reader is referred to subsection 3.3.4 for a detailed representation of the knowledge-based recommender's concept, model and mathematical foundations.

3.2.5 Social Trust Recommendation

One key finding of the previous chapter's qualitative expert interviews may be seen in the fact that investors consider the opinion of other investors in the course of their investment decision-making processes. In particular, the participants mentioned that group investments directed by a lead investor and the general recommendation of early-stage enterprises by other investors may be seen as a common practice in the domain of early-stage enterprise investment. As a consequence, it may be concluded that investors express their connectedness towards other investors as *trust relationships*. Due to the compliance to these reasons, a recommendation system based on human trust, that is, a social recommendation system, may be utilized in the context of early-stage enterprise investment.

As mentioned in the present chapter's background section, social recommendation systems base their recommendation algorithms on explicitly provided trust between users. The *Social Recommendation* algorithm may be seen as a traditional *User-Based Neighbourhood Collaborative Filtering* algorithm but the similarity function is defined as trust relationship between users. On the basis of these implications, trust relationships are utilized in collaborative-filtering techniques to generate personalized recommendations. According to Jamali and Ester [2009, p. 397], trust among users plays an important role in social networks. Therefore, one kind of trust emerges from explicit trust between users, that is, trust among users is stated as directed graph between two users.

Due to the aforementioned aspects and the support by the scientific literature, the authors decide on implementing a social recommender in the course of the present work. The reader is referred to subsection 3.3.5 for a detailed description of the present work's implementation of the social recommender.

3.2.6 Hybrid Recommendation

A very important- and controversial finding of the previous chapter's qualitative- and quantitative research indicates that users actively consolidate other user's opinions on the investment in certain items. However, the research of chapter 2 also indicates that users possess a solidified- and determined opinion on an item's set of preferable attributes as well, possibly restricting other users' influence. A self-contradictory situation arises that upon closer analysis motivates an innovative solution by the utilization of a hybrid recommender that refines a user's preferred list of items by the opinions of other users.

As introduced in the present chapter's background subsection 3.1.1, hybrid recommendation techniques utilize a combination of various other recommenders and calculate the final recommendations by the merge of these techniques according to different aspects. Subsequently, in combination with the facts determined from the paragraph above, that is, a refinement of an existing recommender's recommendations, the emerging constraints highly indicate the utilization of a *pipelined hybridization design*—in particular, a variation of a *cascading hybrid recommender*.

According to Jannach et al. [2010, pp. 138–139], cascading hybrid recommendation algorithms utilize a consecutive list of different recommenders, each refining the rank of the recommendations. Due to its design, only the initial recommender may define a list of items passed on to the other recommendation techniques that, subsequently, are not allowed to exclude existing- or include new items. Additionally, refinements themselves are considered to be of *evolutionary* type, that is, the ranking of the initial list of recommended items shall not be modified too deeply, but rather introduce modest changes. As a consequence, these constraints perfectly match to the previously defined achievable behaviour of a user's recommendation refinement by the utilization of other users' opinions.

Therefore, the authors propose the implementation of a cascading hybrid recommendation algorithm that mainly utilizes the knowledge-based recommender to define a user's list of recommended items and consecutively refines the list's ranking by the application of a user-based collaborative filtering technique, incorporating other users' item recommendations. The reader is referred to subsection 3.3.6 for a detailed representation of the hybrid recommender's concept, model and mathematical foundations.

3.2.7 Recommender System Prototype

One major part of the present research topic lies in the creation of a recommender system prototype in software that implements and comprises all mathematically modelled recommendation algorithms into one single platform. Due to the fact that the implementation of the prototype is affected considerably by the utilized type of recommendation algorithms, the reader is referred to subsection 3.3.7 for a detailed representation of the recommendation system's prototype.

3.3 Design of the Recommender System

In the course of the present section, the reader is informed about the present chapter's results—the implementation of various recommendation algorithms and the crafting of a software prototype, as defined by the methodology's transition from the previous chapter. However, all recommenders share the same underlying (data)model of the present recommendation system and therefore, subsection 3.3.1 describes this model and the recommender system's general functionality in great detail. Independently, the remainder of this section is further organized as follows: Subsections 3.3.2 to 3.3.6 cover the results of one particular recommendation algorithm type each, that is, subsection 3.3.2 comprises *Collaborative Filtering*, subsection 3.3.3 outlines *Content-based Recommendation*, subsection 3.3.4 studies *Knowledge-based Recommendation*, subsection 3.3.5 defines *Social Recommendation* and, consequently, subsection 3.3.6 addresses *Hybrid Recommendation*. Finally, subsection 3.3.7 informs the reader about the constraints of the recommendation system's software prototype.

3.3.1 Model

With the aim of representing the core aspects of the present recommendation system, the remainder of this subsection is divided into four parts, that is, the recommender's domain model, item's attributes, user profile and, finally, user-item interactions. The reader is referred to Figure 3.2 to gain an overview of the system's core model.

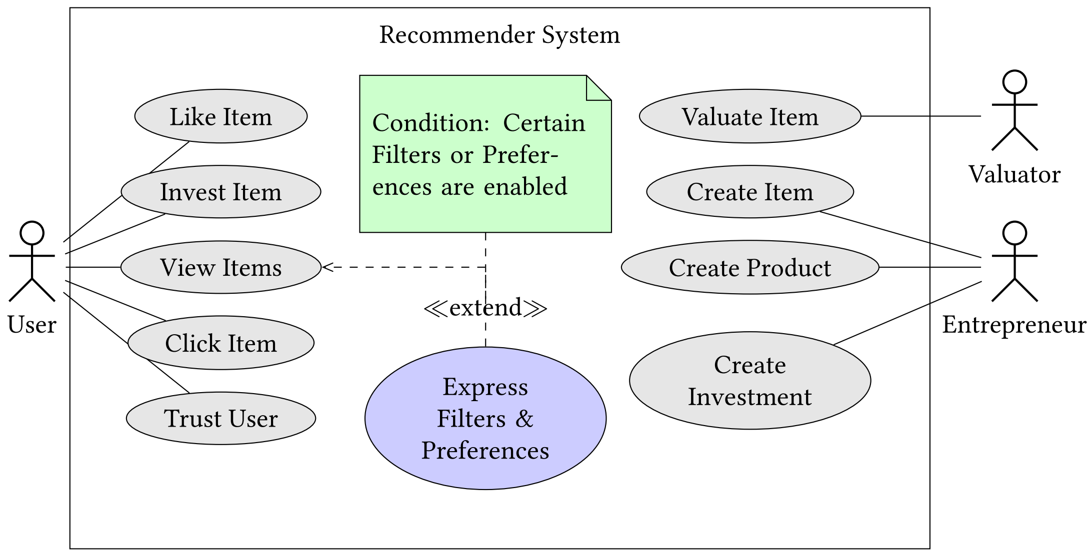

Figure 3.2: Conceptional illustration of the recommender system's model and -functionality on the item entity.

Entities of the System

The present subsection introduces the reader to the different domain model entities that build the basis for the recommendation algorithms and are therefore utilized throughout the present chapter.

Item (Venture) In order to conform to the common recommender systems terminology, the present work will address *ventures* as *items*. Analogously to the importance of the user entity (down below), an *Item* is considered a major part of the recommender system model. In particular, it is the items and their rankings that users are interested in.

User (Investor) In order to conform to the common recommender systems terminology, the present work will address *investors* as *users*. The *User* entity is regarded the major concept in the recommender system model and represents the main interface of interaction between the system and the real world—the investor. The main aim a user tries to achieve, that is, the semantic definition of a user's utility, is stated as gathering a ranked list of items that best fit the user's individual constraints induced by personally defined investment decision-making criteria. As a consequence, a user has two possibilities of interacting with the system:

- Personalized interaction: Participation in the system by providing information utilized by the recommender to generate personalized recommendations.
- Non-personalized interaction: Illustration of items without disclosing personal information. Therefore, the resulting item list does not induce any (personalized) ranking.

Valuator In contrast to the user- and entrepreneur entities, a *Valuator* is a special type of entity that possesses the knowledge to calculate a pre-money valuation of an item on the basis of the item's attributes. In particular, a pre-money valuation may be calculated by the utilization of the scorecard- or berkus methods and expressed as a certain amount of money. Due to the fact that valuators and subsequently, the whole valuation process, is conceptualized independently of the recommendation system, the present chapter will not give any further explanation on that matter.

Entrepreneur The creation of an item and the maintenance of its sub-entities is conducted by the *Entrepreneur*, an entity representing the owners of the item. If an item holds many owners, this set of entrepreneurs is considered a *Team*.

Item Content

Items need *distinguishing features*, for only then will recommenders be capable of calculating certain rankings. Therefore, the reader is referred to the following Table 3.1, which showcases a detailed representation of an item's attributes and the corresponding mathematical symbols that are further utilized in the course of the present chapter.

Table 3.1: Attributes of an item

Attribute	Symbol	Description
Name	–	The name of the item (specified by the entrepreneurs)
Description	–	Internal: The internal description of the item that is only visible to users (specified by the entrepreneurs).
		Public: Description viewable by the public (specified by the entrepreneurs).
City	–	The physical location of the item (specified by the entrepreneurs).
Product	$\mathcal{D}$	An item may possess a set of products or product ideas (provided by the entrepreneurs).
Investment	$\mathcal{D}.\mathcal{Z}$	Each of the item's products may hold a set of investment offerings—specified by the entrepreneurs—allowing users to invest.
Investment Amount	$\mathcal{Z}.Amount$	An investment has a certain investment amount, expressing the amount of money a user needs to invest in order to acquire a certain share of the item.
Investment Share	$\mathcal{Z}.Share$	The share of an item (in percent) a user acquires when investing in the corresponding product of the item.
Valuation	$\mathcal{D}.\mathcal{V}$	Each of the item's products may hold a set of pre-money valuations (specified by valuators).
Valuation Amount	$\mathcal{V}.Amount$	A valuation has a certain pre-money valuation amount, expressing the current worth of the item as amount of money.
Valuation Method	$\mathcal{V}.Method$	The valuation method utilized in the course of the valuation process (either the scorecard- or berkus method).
Date	$Date$	The item's date of creation (specified by the entrepreneurs).
Market Sector	$ms \in \mathcal{M}$	The market sector an item operates in (chosen by the entrepreneurs from a predefined set of market sectors $\mathcal{M}$).

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Attribute	Symbol	Description
Product Interest	$\mathcal{D}.\mathcal{PI}$	Each of the item's products may hold a set of short product descriptions (provided by the entrepreneurs), depicting characteristics of the item in one-word phrases, which are also referred to as *tags*.
Public Interest	$\mathcal{P}$	The interest in the item expressed by the clicking behaviour of possible future customers. This attribute is calculated by the recommender system and influenced by external public viewers not authenticated to the recommendation system.
Team	$\mathcal{E}$	The item's team members represented as a set of entrepreneurs (specified by the entrepreneurs).
Life Cycle	$c \in \mathcal{C}$	The item's current life cycle stage (chosen by the entrepreneurs from a predefined set of life cycle stages $\mathcal{C}$).

User Profile

One of the major use cases of the user may be interpreted as the viewing of items. As already noted in the user's entity description, personalized- and non-personalized interaction with the system is mainly distinguished by the user's provided data on the affection towards certain attributes of items. If a user decides to offer the needed data, the recommendation system ranks the list of items according to the user's disclosed predilection among item attributes. In the course of the present chapter, this particular data is further categorized as *Filters* and *Preferences*. Finally, the user has the possibility to store these categorical settings in a *recommendation profile*, enabling the utilization of *hybrid* recommendation techniques. In particular, this profile holds certain user specified attributes depicted in Table 3.2. The reader is referred to the knowledge-based- and hybrid recommendation algorithms at subsections 3.3.4 and 3.3.6 for a detailed description, an elaboration on application scenarios, implementational specifics of Preferences & Filters and the recommendation profile.

In addition to the process of interacting with items, the user may also interact with other users of the recommendation system in the course of *fellowship*, that is, the explicit definition of trust towards other users. Trust relationships are defined as the crucial component of the social recommender and therefore, the reader is referred to subsection 3.3.5 for details on the implementation of trust in the domain of early-stage enterprise investment.

Table 3.2: Types of a user u's recommendation profile

Symbol	Type	Description
$\mathcal{L}^{\mathrm{D}}$	Boolean	A boolean value enabling the Date preference.
$\mathcal{L}^{\mathrm{HV}}$	Boolean	A boolean value enabling the High Valuation preference.
$\mathcal{L}^{\mathrm{MS}}$	Boolean	A boolean value enabling the Market Sector preference.
$\mathcal{M}^u$	Set	A set of market sectors selected by user u.
$\mathcal{L}^{\textsc{ProdI}}$	Boolean	A boolean value enabling the Product Interest preference.
$\mathcal{PI}^u$	Set	A set of product interests, that is, characteristics of items' products specified in one-word phrases and also referred to as *tags*, specified by user u.
$\mathcal{L}^{\textsc{PubI}}$	Boolean	A boolean value enabling the Public Interest preference.
$\mathcal{L}^{\mathrm{T}}$	Boolean	A boolean value enabling the Team preference.
$\mathcal{L}^{\mathrm{LC}}$	Boolean	A boolean value enabling the Life Cycle preference.
$\mathcal{C}^u$	Set	A set of life cycle stages selected by user u.

User-Item Interactions

One of the key aspects of the recommendation system is stated as the modelling of interactions between the user- and the item entity. These interactions are further referred to as set of *input signals* utilizing the notation $\mathcal{R}$ and are divided into the following set of types: *Likes*, *Investments* and *Clicks*. The prediction of items to a target user is based on $\mathcal{R}$, which may also generically be defined as a set of *ratings* of user u on certain items. More formally, a rating is defined as function $r : \mathcal{U} \times \mathcal{I} \rightarrow \mathcal{D} \mid r \subset \mathcal{U} \times \mathcal{I}$ resulting in the form $r(u, i)$. The definition of $\mathcal{D}$ is dependent on the corresponding *input signals* and distinguished as follows:

(i) Likes (r^L): A user u has the possibility to *like* an item i, which expresses the preference of a user towards a certain item. The set of items liked by user u is defined as $\mathcal{I}^{L,u}$, where $\mathcal{I}^{L,u} \subset \mathcal{I} \ \wedge \ u \in \mathcal{U}$. The ratings structure $\mathcal{D}$ is defined as follows: $\mathcal{D} = \{0, 1\}$.

(ii) Investments (r^I): A user may *invest* once or several times in certain items depending on the availability of products and investment offerings. The set of items invested in by a certain user u is defined as $\mathcal{I}^{I,u}$, where $\mathcal{I}^{I,u} \subset \mathcal{I} \ \wedge \ u \in \mathcal{U}$. The user's utility towards an item is expressed as the number of investments for that very item. Therefore, the ratings structure $\mathcal{D}$ is defined as follows: $\mathcal{D} = \mathbb{N}_0$.

(iii) Clicks (r^C): A user u may *click* certain items, implicitly expressing interest in the corresponding item. The set of items clicked by a certain user u is defined as $\mathcal{I}^{C,u}$, where

$\mathcal{I}^{C,u} \subset \mathcal{I} \ \wedge \ u \in \mathcal{U}$. The ratings structure $\mathcal{D}$ is defined as follows: $\mathcal{D} = \mathbb{N}_0$.

The reader is referred to the collaborative filtering-, content-based- and social recommendation algorithms at subsections 3.3.2, 3.3.3 and 3.3.5 for detailed information on the application of input signals and ratings.

3.3.2 Collaborative Filtering

One of the most commonly utilized approaches in the domain of recommender systems is *collaborative filtering* [Jannach et al., 2010, p. 3]. A collaborative filtering recommendation algorithm utilizes a similarity measure to identify the most similar users or items based on a given ratings database. The reader is referred to the background subsection 3.1.3 for detailed information about the similarity measure and the ratings database. Afterwards, this approach generates predictions for items and, finally, recommends these items to the target user u. The collaborative filtering approaches utilized throughout the present work are divided into two types, that is *User-based-* and an *Item-based Collaborative Filtering*.

User-based Collaborative Filtering

Fundamental elements of a *User-based Neighbourhood Collaborative Filtering* approach are stated as the calculation of similarity between users and the neighbourhood selection process. Subsequently, the user-based similarity's distinguishing features are reflected by certain attributes of the user entity such as the user's *likes*, *investments* or *clicks* on certain items. The following approaches describe the calculation of similarity and the neighbourhood selection process in great detail.

Similarity functions A similarity function is a measurement that computes the similarity between two users, building the basis for the calculation of personalized recommendations. The similarity function's result is defined as real number of the interval $[0, 1]$, whereas 1 states that the target- and investigated entities are *equal* and 0 expresses that both entities entirely *differ* from each other. Each particular similarity function is described as follows:

The Likes similarity calculates the similarity $sim_L(u, u')$ between a set of items $\mathcal{I}^{L,u}$ liked by the target user u and the set of items $\mathcal{I}^{L,u'}$ liked by the peer user u'. The calculation of similarity between users is accomplished by the utilization of the *Jaccard similarity coefficient*. More formally, let $sim_L(u, u')$ be denoted as the *Likes* similarity function of user u and a peer user u', where

$$sim_L(u, u') = J\left(\mathcal{I}^{L,u}, \mathcal{I}^{L,u'}\right) = \frac{\left|\mathcal{I}^{L,u} \cap \mathcal{I}^{L,u'}\right|}{\left|\mathcal{I}^{L,u} \cup \mathcal{I}^{L,u'}\right|} \tag{3.4}$$

holds.

The Investments similarity calculates the similarity $sim_I(u, u')$ between a set of items $\mathcal{I}^{I,u}$ invested by the target user u and the set of items $\mathcal{I}^{I,u'}$ invested by the peer user u'. The calculation of similarity between users is accomplished by the utilization of the *Cosine similarity coefficient*, whereas the sets $\mathcal{I}^{I,u}$ and $\mathcal{I}^{I,u'}$ are represented as vectors depicting the number of investments of both users for the corresponding sets of items. More formally, let $sim_I(u, u')$ be denoted as the *Investments* similarity function of user u and a peer user u', where

$$sim_I(u, u') = \cos\left(\mathcal{I}^{I,u}, \mathcal{I}^{I,u'}\right) = \frac{\left\langle \mathcal{I}^{I,u}, \mathcal{I}^{I,u'} \right\rangle}{|\mathcal{I}^{I,u}| * |\mathcal{I}^{I,u'}|} \tag{3.5}$$

holds.

The Clicks similarity calculates the similarity $sim_C(u, u')$ between a set of items $\mathcal{I}^{C,u}$ clicked by the target user u and the set of items $\mathcal{I}^{C,u'}$ clicked by the peer user u'. The calculation of similarity between users is accomplished by the utilization of the *Jaccard similarity coefficient*. More formally, let $sim_C(u, u')$ be denoted as the *Clicks* similarity function of user u and a peer user u', where

$$sim_C(u, u') = J\left(\mathcal{I}^{C,u}, \mathcal{I}^{C,u'}\right) = \frac{\left|\mathcal{I}^{C,u} \cap \mathcal{I}^{C,u'}\right|}{|\mathcal{I}^{C,u} \cup \mathcal{I}^{C,u'}|} \tag{3.6}$$

holds.

Neighbourhood formation In the course of the User-based Collaborative Filtering approach, neighbours are peer users, whose historical interests are similar to those of the target user. More formally, a peer user u' is denoted as ***neighbour*** of user u, if u' is similar to u. Therefore, the neighbourhood function $N(u)$ reduces the set of peer users taken as input to the recommendation algorithm. According to Sarwar et al. [2001], the selection of an appropriate threshold plays a crucial role for the prediction quality of a neighbourhood collaborative filtering algorithm. Therefore, in order for a peer user to be included in the neighbourhood of the target user, the corresponding similarity function needs to reach or exceed a certain threshold. A detailed discussion about choosing an appropriate threshold can be found in the background subsection 3.1.3 or in Jannach et al. [2010, pp. 17–18] and Gedikli [2013, p. 11]. One finding of the present work's previous chapter 2 indicates that ratings data in the domain of early-stage enterprise investment is considerably sparse. Due to this reason, the threshold of all subsequent neighbourhood functions is set to the real number 0.7. The mathematical notations of the neighbourhood functions are described as follows:

The Likes neighbourhood $N_L(u)$ function is denoted as neighbourhood of user u, where

$$N_L(u) = \{\ u' \ \in\ U \setminus u \ :\ sim_L(u, u') \geq 0.7\} \tag{3.7}$$

holds.

The Investments neighbourhood $N_I(u)$ function is denoted as neighbourhood of user u, where

$$N_I(u) = \{\ u' \ \in \ U \setminus u \ : \ sim_I(u, u') \geq 0.7\} \tag{3.8}$$

holds.

The Clicks neighbourhood $N_C(u)$ function is denoted as neighbourhood of user u, where

$$N_C(u) = \{\ u' \ \in \ U \setminus u \ : \ sim_C(u, u') \geq 0.7\} \tag{3.9}$$

holds.

Recommendation Algorithms Typically, the *prediction* or *score* of items to a user is formally expressed as a *utility function* of the form $S : Users \times Items \rightarrow \mathbb{R}_{\geq 0} \mid R \subset Users \times Items$ [Gediminas Adomavicius, Manouselis, and Kwon, 2011, pp. 769–770]. Subsequently, the adaptation to the present work is stated as $S : \mathcal{U} \times \mathcal{I} \rightarrow \mathbb{R}_{\geq 0} \mid S \subset \mathcal{U} \times \mathcal{I}$. Without loss of generality, it shall be defined that a user u is capable of knowing whether a certain item recommendation is appropriate and therefore, user u knows *if* a certain item i belongs to the personal set of likeable items. Subsequently, the main task of the recommendation algorithm is to construct a ranked list, such that the utility function $S(u, i)$ is maximized.

The final ordered item recommendation set comprises a certain amount of items that constitute a high probability of being liked by the target user. The ranking set is based on each item's utility calculated by the utility function S in a descending order. The prediction algorithms utilized by the present work are elaborated based on mathematical formulations as follows:

The Likes algorithm (UB^L) calculates the utility of a target item based on a weighted factor that depends on the similarity of the peer users and their rankings of the target item. Finally, item recommendations are calculated based on the liked items of the target user's neighbourhood and weighted by the similarities and item occurrences of the corresponding peer user. More formally, the recommender is defined as follows:

$$S^{UB^L}(u, i) = \frac{\sum\limits_{u' \in N(u)} sim(u, u') \cdot r^L(u', i)}{|N(u)|} \tag{3.10}$$

where u is defined as the target user, u' is stated as the investigated (peer) user, i is specified as the target item, $sim(u, u') \in \{sim_L(u, u'), sim_I(u, u'), sim_C(u, u')\}$ is stated as similarity function and $N(u) \in \{N_L(u), N_I(u), N_C(u)\}$ is defined as the corresponding user neighbourhood of user u.

The Investments algorithm (UB^I) calculates the utility of a target item based on a weighted factor that depends on the similarity of the peer users and their rankings of the target item. Finally, item recommendations are calculated based on the invested items of the target user's neighbourhood and weighted by the similarities and item investments of the corresponding peer user. More formally, the recommender is defined as follows:

$$S^{UB^I}(u,i) = \frac{\sum\limits_{u' \in N(u)} sim(u,u') \cdot r^I(u',i)}{\sum\limits_{u' \in N(u)} sim(u,u')} \tag{3.11}$$

where u is defined as the target user, u' is stated as the investigated (peer) user, i is specified as the target item, $sim(u,u') \in \{sim_L(u,u'), sim_I(u,u'), sim_C(u,u')\}$ is stated as the similarity function and $N(u) \in \{N_L(u), N_I(u), N_C(u)\}$ is defined as the corresponding user neighbourhood of user u.

The Clicks algorithm (UB^C) calculates the utility of a target item based on a weighted factor that depends on the similarity of the peer users and their rankings of the target item. Finally, item recommendations are calculated based on the clicked items of the target user's neighbourhood and weighted by the similarities and item clicks of the corresponding peer user. More formally, the recommender is defined as follows:

$$S^{UB^C}(u,i) = \frac{\sum\limits_{u' \in N(u)} sim(u,u') \cdot r^C(u',i)}{\sum\limits_{u' \in N(u)} sim(u,u')} \tag{3.12}$$

where u is defined as the target user, u' is stated as the investigated (peer) user, i is specified as the target item, $sim(u,u') \in \{sim_L(u,u'), sim_I(u,u'), sim_C(u,u')\}$ is stated as the similarity function and $N(u) \in \{N_L(u), N_I(u), N_C(u)\}$ is defined as the corresponding user neighbourhood of user u.

Item-based Collaborative Filtering

Analogously to user-based neighbourhood collaborative filtering, the calculation of similarity between items and the neighbourhood selection process are regarded fundamental procedures of the *Item-based Neighbourhood Collaborative Filtering* approach. Subsequently, the item-based similarity's distinguishing features are reflected by certain attributes of the user entity, such as the user's *likes*, *investments* or *clicks* on certain items. The following approaches describe the calculation of similarity and the neighbourhood selection process in great detail.

Similarity functions A similarity function is a measurement that computes the similarity between two items, building the basis for the calculation of personalized recommendations. The similarity function's result is defined as real number of the interval $[0, 1]$, whereas 1 states that the target- and investigated entities are *equal* and 0 expresses that both entities entirely *differ* from each other. Each particular similarity function is described as follows:

The Likes similarity calculates the similarity $sim_L(i, i')$ between a set of users $\mathcal{U}^{L,i}$ who liked the target item i and the set of users $\mathcal{U}^{L,i'}$ who liked the peer item i'. The calculation of similarity between items is accomplished by the utilization of the *cosine similarity coefficient*. More formally, let $sim_L(i, i')$ be denoted as the *Likes similarity* function of item i and a peer item i', where

$$sim_L(i, i') = \cos\left(\mathcal{U}^{L,i}, \mathcal{U}^{L,i'}\right) = \frac{\left\langle \mathcal{U}^{L,i}, \mathcal{U}^{L,i'} \right\rangle}{|\mathcal{U}^{L,i}| * |\mathcal{U}^{L,i'}|} \tag{3.13}$$

holds.

The Investments similarity calculates the similarity $sim_I(i, i')$ between a set of users $\mathcal{U}^{I,i}$ who invested in the target item i and the set of users $\mathcal{U}^{I,i'}$ who invested in the peer item i'. The calculation of similarity between items is accomplished by the utilization of the *cosine similarity coefficient*. More formally, let $sim_I(i, i')$ be denoted as the *Investments similarity* function of item i and a peer item i', where

$$sim_I(i, i') = \cos\left(\mathcal{U}^{I,i}, \mathcal{U}^{I,i'}\right) = \frac{\left\langle \mathcal{U}^{I,i}, \mathcal{U}^{I,i'} \right\rangle}{|\mathcal{U}^{I,i}| * |\mathcal{U}^{I,i'}|} \tag{3.14}$$

holds.

The Clicks similarity calculates the similarity $sim_C(i, i')$ between a set of users $\mathcal{U}^{I,i}$ who clicked the target item i and the set of users $\mathcal{U}^{I,i'}$ who clicked the peer item i'. The calculation of similarity between items is accomplished by the utilization of the *cosine similarity coefficient*. More formally, let $sim_C(i, i')$ be denoted as the *Clicks similarity* function of item i and a peer item i', where

$$sim_C(i, i') = \cos\left(\mathcal{U}^{C,i}, \mathcal{U}^{C,i'}\right) = \frac{\left\langle \mathcal{U}^{C,i}, \mathcal{U}^{C,i'} \right\rangle}{|\mathcal{U}^{C,i}| * |\mathcal{U}^{C,i'}|} \tag{3.15}$$

holds.

Neighbourhood formation In the course of the Item-based Collaborative Filtering approach, neighbours are the transpose of the user-based neighbours. More formally, a peer item i' is denoted as *neighbour* of item i, if i' is similar to i. The neighbourhood function $N(i)$ reduces the set of peer items taken as input to the recommendation algorithm. According to Sarwar et al. [2001], the selection of an appropriate threshold plays a crucial role for the prediction quality of a neighbourhood collaborative filtering algorithm. Therefore, in order for a peer item to be included in the neighbourhood of the target item, the corresponding similarity function needs to reach or exceed a certain threshold. A detailed discussion about choosing an appropriate threshold can be found in the background subsection 3.1.3 or in Jannach et al. [2010, pp. 17–18] and Gedikli [2013, p. 11]. One finding of the present work's previous chapter 2 indicates that ratings data in the domain of early-stage enterprise investment is considerably sparse. Due to this reason, the threshold of all subsequent neighbourhood functions is set to the real number 0.7. The mathematical notations of the neighbourhood functions are described as follows:

The Likes neighbourhood $N_L(i)$ function is denoted as neighbourhood of item i, where

$$N_L(i) = \{\ i' \ \in\ I \setminus i\ :\ sim_L(i,i') \geq 0.7\} \tag{3.16}$$

holds.

The Investments neighbourhood $N_I(i)$ function is denoted as neighbourhood of item i, where

$$N_I(i) = \{\ i' \ \in\ I \setminus i\ :\ sim_I(i,i') \geq 0.7\} \tag{3.17}$$

holds.

The Clicks neighbourhood $N_C(i)$ function is denoted as neighbourhood of item i, where

$$N_C(i) = \{\ i' \ \in\ I \setminus i\ :\ sim_C(i,i') \geq 0.7\} \tag{3.18}$$

holds.

Recommendation Algorithms The main task of the recommendation algorithm is stated as the construction of a ranked list, such that the utility function $S(u,i)$ is maximized. The final ordered item recommendation set comprises a certain amount of items that constitute a high probability of being liked by the target user. The ranking set is based on each item's utility calculated by the utility function S and sorted in a descending order. The prediction algorithms utilized by the present work are elaborated based on mathematical formulations as follows:

The Likes algorithm (IB^L) calculates the utility of a target item based on a weighted average factor that depends on the similarity and the ranking of the corresponding peer item. In the course of the item-based approach, peer items are considered for similarity calculation rather than peer users. Finally, item recommendations are calculated based on the liked items of the target item's neighbourhood and weighted by the similarity and the item likings of the corresponding peer item. More formally, the recommender is defined as follows:

$$S^{IB^L}(u,i) = \frac{\sum\limits_{i' \in N(i)} sim(i,i') \cdot r^L(u,i')}{|N(i)|} \tag{3.19}$$

where u is defined as the target user, i is specified as the investigated item, i' is stated as the investigated peer item, $sim(i,i') \in \{sim_L(i,i'), sim_I(i,i'), sim_C(i,i')\}$ is specified as the similarity function and $N(i) \in \{N_L(i), N_I(i), N_C(i)\}$ is defined as the corresponding item neighbourhood of the investigated item i.

The Investments algorithm (IB^I) calculates the utility of a target item based on a weighted average factor that depends on the similarity and the ranking of the corresponding peer item. In the course of the item-based approach, peer items are considered for similarity calculation rather than peer users. Finally, item recommendations are calculated based on the invested items of the target item's neighbourhood and weighted by the similarity and the item investments of the corresponding peer item. More formally, the recommender is defined as follows:

$$S^{IB^I}(u,i) = \frac{\sum\limits_{i' \in N(i)} sim(i,i') \cdot r^I(u,i')}{|N(i)|} \tag{3.20}$$

where u is defined as the target user, i is specified as the investigated item, i' is stated as the investigated peer item, $sim(i,i') \in \{sim_L(i,i'), sim_I(i,i'), sim_C(i,i')\}$ is specified as the similarity function and $N(i) \in \{N_L(i), N_I(i), N_C(i)\}$ is defined as the corresponding item neighbourhood of the investigated item i.

The Clicks algorithm (IB^C) calculates the utility of a target item based on a weighted average factor that depends on the similarity and the ranking of the corresponding peer item. In the course of the item-based approach, peer items are considered for similarity calculation rather than peer users. Finally, item recommendations are calculated based on the clicked items of the target item's neighbourhood and weighted by the similarity and the item clicks of the corresponding peer item. More formally, the recommender is defined as follows:

$$S^{IB^C}(u,i) = \frac{\sum\limits_{i' \in N(i)} sim(i,i') \cdot r^C(u,i')}{|N(i)|} \tag{3.21}$$

where u is defined as the target user, i is specified as the investigated item, i' is stated as the investigated peer item, $sim(i,i') \in \{sim_L(i,i'), sim_I(i,i'), sim_C(i,i')\}$ is specified as the similarity function and $N(i) \in \{N_L(i), N_I(i), N_C(i)\}$ is defined as the corresponding item neighbourhood of the investigated item i.

3.3.3 Content-based Recommendation

Content-based Recommendation—which is also referred to as *Content-based Filtering*—is solely based on the user's personal interest in an item. Therefore, its major concept is defined as content comparison between historically interested items and new ones, that is, unknown items. Subsequently, those not yet known items maximizing the target user's utility are recommended. The basis for determining similarity in the context of content-based filtering is stated as content comparison between certain attributes of the user's historically interested items and the corresponding attributes of peer items not yet known to the user (the reader is referred to subsection 3.3.1 for a detailed description of an item's model). The following approaches describe the calculation process of the content-based algorithm in detail.

User Profile

In the content-based filtering approach the *User Profile* is represented as a virtual item including all *Product Interest*, *Market Sector* and *Life Cycle* attributes merged among all of user u's historic item interests. The reader is referred to Table 3.2 for a detailed description of the attributes.

Product Interest The present content-based filtering implementation considers an item's product tags in order to compute similarity between items. A set of an item's products' tags $u.\mathcal{PI}$ of the liked items of the target user u is stated by the following equation:

$$u.\mathcal{PI} = \bigcup_{i \in I^{L,u}} \{(\forall d \in i.\mathcal{D})\,[d.\mathcal{PI}]\} \tag{3.22}$$

where u is defined as the target user, i is specified as the historically liked item of the target user u, $\mathcal{PI}$ is defined as the set of product tags and $\mathcal{D}$ is stated as a product.

Market Sector The present content-based filtering implementation considers an item's market sectors in order to compute similarity between items. A set of market sectors $u.\mathcal{M}$ of liked items of the target user u is stated by the following equation:

$$u.\mathcal{M} = \bigcup_{i \in I^{L,u}} \{(\forall ms \in i.\mathcal{M})\,[ms]\} \tag{3.23}$$

where u is defined as the target user, i is specified as the historically liked item of the target user u and $\mathcal{M}$ is defined as the set of market sectors.

Life Cycle The present content-based filtering implementation considers an item's life cycle in order to compute similarity between items. A set of life cycles $u.\mathcal{C}$ of liked items of the target user u is stated by the following equation:

$$u.\mathcal{C} = \bigcup_{i \in I^{L,u}} \{(\forall c \in i.\mathcal{C})\,[c]\} \tag{3.24}$$

where u is defined as the target user, i is specified as the historically liked item of the target user u, $\mathcal{C}$ is defined as the set of life cycles.

Recommendation Algorithm

The main task of the recommendation algorithm is stated as the calculation of a ranked list, such that the utility function $S^{CB}(u,i)$ is maximized. The final ordered item recommendation set comprises a certain amount of items that constitute a high probability of being liked by the target user. The ranking of this set is based on each item's utility calculated by the utility function S^{CB} and sorted in descending order. The whole utility function S^{CB}'s calculation is based on the computation of the previously introduced attributes and, subsequently, the corresponding similarity functions. Therefore, the *similarity functions* and, ultimately, the recommendation algorithm are described in great detail as follows:

Product Interest similarity The Product Interest similarity function calculates the similarity between items based on the *Jaccard Similarity Coefficient*. More formally, let

$sim_{\mathcal{PI}}(u.\mathcal{PI}, i'.\mathcal{D}.\mathcal{PI})$ be denoted as the *Product Interest similarity* function utilizing product tags of items historically liked by user u and the peer item i''s product tags $i'.\mathcal{D}.\mathcal{PI}$, where

$$sim_{\mathcal{PI}}\left(u.\mathcal{PI}, i'.\mathcal{D}.\mathcal{PI}\right) = J\left(u.\mathcal{PI}, i'.\mathcal{D}.\mathcal{PI}\right) = \frac{|u.\mathcal{PI} \cap i'.\mathcal{D}.\mathcal{PI}|}{|u.\mathcal{PI} \cup i'.\mathcal{D}.\mathcal{PI}|} \tag{3.25}$$

holds.

Market sector similarity The Market sector similarity function calculates the similarity between items based on the *Jaccard Similarity Coefficient.* More formally, let $sim_{\mathcal{M}}(u.\mathcal{M}, i'.\mathcal{M})$ be denoted as the *Market Sector similarity* function utilizing market sectors of items historically liked by user u and the peer item i''s market sector $i'.\mathcal{M}$, where

$$sim_{\mathcal{M}}\left(u.\mathcal{M}, i'.\mathcal{M}\right) = J\left(u.\mathcal{M}, i'.\mathcal{M}\right) = \frac{|u.\mathcal{M} \cap i'.\mathcal{M}|}{|u.\mathcal{M} \cup i'.\mathcal{M}|} \tag{3.26}$$

holds.

Life cycle similarity The Life cycle similarity function calculates the similarity between items based on the *Jaccard Similarity Coefficient.* More formally, let $sim_{\mathcal{C}}(u.\mathcal{C}, i'.\mathcal{C})$ be denoted as the *Life Cycle similarity* function utilizing distinct life cycles of items historically liked by user u and the peer item i''s life cycle $i'.\mathcal{C}$, where

$$sim_{\mathcal{C}}\left(u.\mathcal{C}, i'.\mathcal{C}\right) = J\left(u.\mathcal{C}, i'.\mathcal{C}\right) = \frac{|u.\mathcal{C} \cap i'.\mathcal{C}|}{|u.\mathcal{C} \cup i'.\mathcal{C}|} \tag{3.27}$$

holds.

Finally, the recommendation algorithm calculates item i''s utility to the target user u based on the average score of all individual similarities each weighted by an individual importance factor w. This factor is derived from the findings of the present work's previous chapter 2 stating that the market sector is more important than the life cycle and, in turn, the life cycle is more important than product tags. Finally, the recommender is defined as follows:

$$\begin{aligned} S^{CB}(u, i') = \ & \frac{sim_{\mathcal{PI}}(u.\mathcal{PI}, i'.\mathcal{D}.\mathcal{PI}) \cdot w_{\mathcal{PI}}}{3} \\ & + \frac{sim_{\mathcal{M}}(u.\mathcal{M}, i'.\mathcal{M}) \cdot w_{\mathcal{M}}}{3} \\ & + \frac{sim_{\mathcal{C}}(u.\mathcal{C}, i'.\mathcal{C}) \cdot w_{\mathcal{C}}}{3} \end{aligned} \tag{3.28}$$

where u is defined as the target user, i' is specified as the investigated item, $sim_{\mathcal{PI}}(u.\mathcal{PI}, i'.\mathcal{D}.\mathcal{PI})$, $sim_{\mathcal{M}}(u.\mathcal{M}, i'.\mathcal{M})$, $sim_{\mathcal{C}}(u.\mathcal{C}, i'.\mathcal{C})$ are stated as individual similarities and $w_{\mathcal{PI}} = 0.2$, $w_{\mathcal{M}} = 0.5$, $w_{\mathcal{C}} = 0.3$ are defined as statically set weighting factors summing up to the integer 1.

3.3.4 Knowledge-based Recommendation

The major concept of the knowledge-based recommender in the context of the present work is based on an item's *properties* and the sets of *filters* Φ and *preferences* Π. Generally speaking, each filter or preference matches certain filter- or preference *attributes* provided by the target user to the corresponding properties of each item (the reader is referred to subsection 3.3.1 for a detailed representation of an item's model). Whereas a filter excludes items from the set of recommended items if the constraints of the user defined filter parameters are not fulfilled, a preference may generally be seen as an option to sort the set of recommended items based on the individual preference settings defined by the target user. It is important to note that filters are considered *hard constraints* that need to be fulfilled entirely by an item in order to be included in the list of recommended items. In contrast, each preference setting is weighted, that is, the user has the possibility to set an importance parameter on each selected preference individually. Finally, according to the user's selected and specified filters or preferences—which may also be considered *decision rules*—the knowledge-based recommender computes and ranks items that are most probably being liked by the user.

Filters

The first major aspect of the knowledge-based recommender is stated as the set of *filters* Φ that —in contrast to preferences—are regarded *hard constraints*, having the need of being fulfilled by an item in order to even be included in the recommendation list. However, filters are also based on certain user specified attributes $\mathcal{L}^{\Phi}$. From a process-oriented perspective, the application of filters directly influences the base set of items $\mathcal{I}$ that may be further utilized for recommendation in the course of the selection of preferences. Therefore, the formal representation of the output of a filter $\phi \in \Phi$ is defined as the set $\mathcal{I}^{\phi} \subset \mathcal{I}$ and calculated as follows:

$$\mathcal{I}^{\phi} = \phi(\mathcal{I}, \mathcal{L}^{\phi}) \tag{3.29}$$

where ϕ is defined as function $\phi : \mathcal{I}, \mathcal{L}^{\phi} \rightarrow \mathcal{I}^{\phi}$ and $\mathcal{L}^{\phi} \subset \mathcal{L}^{\Phi}$ is stated as filter ϕ's set of attributes specified by the user.

One major design criterion of the knowledge-based recommender is stated as user u's freedom of choice in the context of the selection of preferences and filters. As a consequence, filters need to be user selectable on an individual basis. However, this aspect also implies that multiple filters may be selected by user u at the same time. In order to address this situation, the filter component of the knowledge-based recommender merges the output of each user selected filter by *intersection*, more formally:

$$\mathcal{I}^{\Phi^u} = \bigcap_{\phi \in \Phi^u} \phi(\mathcal{I}, \mathcal{L}^{\phi}) \tag{3.30}$$

where $\Phi^u \subset \Phi$ is defined as the set of filters selected by user u and $\mathcal{I}^{\Phi^u}$ is stated as the intersected output of all filter functions that depend on $\phi \in \Phi^u$, $\mathcal{I}$ and $\mathcal{L}^{\phi}$.

On the basis of Notation (3.29), the algorithms of each filter ϕ and the utilized set of user defined attributes $\mathcal{L}^{\phi}$ are depicted in detail in the following listing (the reader is referred to subsection 3.3.1 for information on the utilized attributes):

(i) Investment Range (ϕ_{IR}): The input to this filter is a user defined *investment amount range* defined by a minimum/maximum interval. The filter itself includes a certain item i in the result set, if there exists at least one investment for at least one of item i's products that has an investment amount lying within a user defined investment amount range. More formally, ϕ_{IR} is defined as follows:

$$\begin{aligned}\mathcal{I}^{\text{IR}} &= \phi_{\text{IR}}\left(\mathcal{I}, \mathcal{L}^{\text{IR}}\right)\\ &= \{i \in \mathcal{I} \,:\, (\exists d \in i.\mathcal{D})\,(\exists z \in d.\mathcal{Z})[\,MinAmount \leq z.Amount \leq MaxAmount]\,\}\end{aligned} \tag{3.31}$$

where $\mathcal{I}^{\text{IR}} \subset \mathcal{I}$ is considered the set of items calculated by the ϕ_{IR} function, $i.\mathcal{D}$ conforms to item i's set of products whereas $d \in \mathcal{D}$ is stated as one particular product of item i. Furthermore, $d.\mathcal{Z}$ is the set of product d's investment offerings whereas $z \in d.\mathcal{Z}$ is stated as one particular investment of product d. Additionally, $z.Amount$ is defined as a particular investment money offering's amount of money specified by item i. Finally, $MinAmount$ to $MaxAmount$ is stated as user u's specified investment amount range of the interval $[a, b] = \{a \in \mathbb{R}_{\geq 0}, b \in \mathbb{R}_{\geq 0} : a \leq b\}$ and is therefore considered the present filter's set of attributes $\mathcal{L}^{\text{IR}} = \{MinAmount, MaxAmount\}$.

(ii) Share Range (ϕ_{SR}): In analogy to the previous filter function, the input to the Share Range filter is a user defined *investment share range* defined by a minimum/maximum interval. The filter itself includes a certain item i in the result set, if there exists at least one investment for at least one of item i's products that has an investment share lying within a user defined investment share range. More formally, ϕ_{SR} is defined as follows:

$$\begin{aligned}\mathcal{I}^{\text{SR}} &= \phi_{\text{SR}}\left(\mathcal{I}, \mathcal{L}^{\text{SR}}\right)\\ &= \{i \in \mathcal{I} \,:\, (\exists d \in i.\mathcal{D})\,(\exists z \in d.\mathcal{Z})[\,MinShare \leq z.Share \leq MaxShare]\,\}\end{aligned} \tag{3.32}$$

where $\mathcal{I}^{\text{SR}} \subset \mathcal{I}$ is considered the set of items calculated by the ϕ_{SR} function. Furthermore, $z.Share$ is defined as a particular investment share offering's amount specified by item i. Finally, $MinShare$ to $MaxShare$ is stated as user u's specified investment share range of the interval $[a, b] = \{a \in \mathbb{Z}_{\geq 0}, b \in \mathbb{Z}_{\geq 0} : 0 \leq a \leq b \leq 100\}$ (in percent) and is therefore considered the present filter's set of attributes $\mathcal{L}^{\text{SR}} = \{MinShare, MaxShare\}$.

(iii) Valuation Range (ϕ_{VR}): Analogously to the previous filter functions, the input to the Valuation Range filter is a user defined *pre-money valuation amount range* defined by a minimum/maximum interval. The filter itself includes a certain item i in the result set, if there exists a valuation for at least one of item i's products that has a pre-money valuation amount lying within a user specified pre-money valuation range. More formally, ϕ_{VR} is defined as follows:

$$\begin{aligned}\mathcal{I}^{\text{VR}} &= \phi_{\text{VR}}\left(\mathcal{I}, \mathcal{L}^{\text{VR}}\right)\\ &= \{i \in \mathcal{I} \,:\, (\exists d \in i.\mathcal{D})\,(\exists v \in d.\mathcal{V})[\,MinVal \leq v.Amount \leq MaxVal]\,\}\end{aligned} \tag{3.33}$$

where $\mathcal{I}^{\text{VR}} \subset \mathcal{I}$ is considered the set of items calculated by the ϕ_{VR} function, $i.\mathcal{D}$ conforms to item i's set of products whereas $d \in \mathcal{D}$ is stated as one particular product of item i. Furthermore, $d.\mathcal{V}$ is the set of product d's valuations whereas $v \in d.\mathcal{V}$ is stated as one particular valuation of product d. Additionally, $v.Amount$ is defined as a particular pre-money valuation's amount held by the system. Finally, $MinVal$ to $MaxVal$ is stated as user u's specified pre-money valuation amount range of the interval $[a, b] = \{a \in \mathbb{R}_{\geq 0}, b \in \mathbb{R}_{\geq 0} : a \leq b\}$ and is therefore considered the present filter's set of attributes $\mathcal{L}^{\text{VR}} = \{MinVal, MaxVal\}$.

(iv) Valuation Method (ϕ_{VM}): In contrast to the previous filter functions, the input to the Valuation Method filter is a user defined set of *valuation methods* that are matched against existing valuations for products of item i. The filter itself includes a certain item i in the result set, if there exists a valuation for at least one of item i's products that was rated utilizing a pre-money valuation method being an element of a user specified set of valuation methods. More formally, ϕ_{VM} is defined as follows:

$$\begin{aligned} \mathcal{I}^{\text{VM}} &= \phi_{\text{VM}}\left(\mathcal{I}, \mathcal{L}^{\text{VM}}\right) \\ &= \{i \in \mathcal{I} \,:\, (\exists d \in i.\mathcal{D})\,(\exists v \in d.\mathcal{V})[\,v.Method \in \mathcal{VM}]\,\} \end{aligned} \tag{3.34}$$

where $\mathcal{I}^{\text{VM}} \subset \mathcal{I}$ is considered the set of items calculated by the ϕ_{VM} function. Furthermore, $v.Method$ is considered pre-money valuation v's valuation method. Finally, $\mathcal{VM}$ is the set of valuation methods specified by user u that complies to the variations depicted by the *power set* $\wp(\{scorecard, berkus\})$ and is therefore considered the present filter's set of attributes $\mathcal{L}^{\text{VM}} = \mathcal{VM}$.

Preferences

The second major aspect of the knowledge-based recommender's recommendation algorithm is the modelling of preferences that induce a ranking of items. The knowledge-based recommender enables the user to select a set of various preferences and assign each of which an individual *importance* rating—a weight—that expresses the user's utility towards a certain preference. Finally, the aggregation of each user specified preference's item rankings is accomplished by the implementation of a *Weighted Borda count*—a variation of a vote-counting scheme in the area of *collective decision-making*.

The Preference Function The first step of the knowledge-based recommender in the context of preferences is stated as the calculation of ranked item lists corresponding to the user specified preferences and their attributes. The semantics of the rank itself are defined as follows: Let preference π induce a *strict weak order* $<_\pi$ over a set of items. The authors denote that an item i is preferred over—that is, *of higher utility* than—another item j in the context of preference π as $i <_\pi j$. Subsequently, in the case of indifference among items with respect to preference π, that is, two items are incomparable, the following notation is denoted: $i \sim_\pi j$. Due to illustration purposes, the combination of the mentioned notations is denoted as $i \lesssim_\pi j$ stating that item i

is either preferred over- or indifferent from item j. This particular ordering scheme enables the assignment of ranks—consecutive natural numbers starting from 1—to items.

User u's individual rank for item i utilizing preference π among a certain set of items $\mathcal{I}$ is defined as follows:

$$\rho_{i,\pi,\mathcal{I}} = \pi(i, \mathcal{L}^{\pi}, \mathcal{I}) \tag{3.35}$$

where $\rho_{i,\pi,\mathcal{I}}$ is specified as the individual rank of user u's preference π for item i in the domain of $\mathcal{I}$, π is defined as the function $\pi : i, \mathcal{L}^{\pi}, \mathcal{I} \to \{n \in \mathbb{Z}_{>0} : 0 < n \leq |\mathcal{I}|\}$ resulting in the form $\pi(i, \mathcal{L}^{\pi}, \mathcal{I})$ and $\mathcal{L}^{\pi}$ is stated as user defined set of attribute values corresponding to preference π's domain of attributes.

In order to calculate the rank of a set of items $\mathcal{I}$ in the course of a certain preference π, a new data structure needs to be introduced with the purpose of expressing the rank $\rho_{i,\pi,\mathcal{I}}$ of an item i among a set of other items $\mathcal{I} \setminus i$. Let $\mathcal{I}^{\pi}$ be denoted as a set of ordered pairs $(i, \rho_{i,\pi,\mathcal{I}})$, more formally: $\mathcal{I}^{\pi} = \{(i, \rho_{i,\pi,\mathcal{I}}) : i \in \mathcal{I}, \rho_{i,\pi,\mathcal{I}} \in \{n \in \mathbb{Z}_{>0} : 0 < n \leq |\mathcal{I}|\}\}$.

Due to the fact that—from a process-oriented point of view—a preference π is interpreted as a function calculating a ranked list of items, each preference $\pi \in \Pi$ may utilize individual logic depending on the corresponding input factors (attributes) in order to calculate the rank among each item $i \in \mathcal{I}$. Therefore, the algorithms of each preference $\pi \in \Pi$ and, subsequently, the utilized set of attributes $\mathcal{L}^{\pi}$ are described in detail in the following listing (the reader is referred to subsection 3.3.1 for information on the utilized attributes):

(i) Date (π_{D}): The Date preference ranks item i in context to the domain of all items $\mathcal{I} \setminus i$ based on i's date of creation—that is, $i.Date$—whereas more recent dates are ranked better than their older counterparts. Due to the fact that the Date preference does not rely upon any user specified input, this preference's user specified set of attributes is defined as $\mathcal{L}^{\text{D}} = \emptyset$.

(ii) High Valuation (π_{HV}): The basis for the High Valuation preference is stated as the average pre-money valuations for item i in the context of the domain of all items $\mathcal{I} \setminus i$. A higher average valuation is ranked better than its lower counterparts. Analogously to the previous Date preference, the present High Valuation preference does not rely upon any user specified input. Therefore, this preference's user specified set of attributes is defined as $\mathcal{L}^{\text{HV}} = \emptyset$.

(iii) Market Sector (π_{MS}): The input to this preference is a user selected subset of a predefined set of market sectors—that is, $\mathcal{L}^{\text{MS}} = \mathcal{M}^u \subset \mathcal{M}$—that are matched to item i's defined market sector. Matching itself is accomplished by the calculation of the Jaccard correlation coefficient between the set of selected market sectors and item i's actual market sector. In the context of the domain of all items $\mathcal{I} \setminus i$, item i is ranked better, if its calculated Jaccard correlation coefficient is higher than the ones of the other items or lower analogously.

(iv) Product Interest (π_{ProdI}): The input to this preference is a user defined set of *tags*—short one-word phrases describing the item—and therefore, $\mathcal{L}^{\text{ProdI}} = \mathcal{PI}^u$. Matching itself is accomplished by the calculation of the Jaccard correlation coefficient between the set of user defined tags $\mathcal{PI}^u$ and the set of tags of each of item i's products. Subsequently, the highest Jaccard correlation coefficient among item i's products is selected. In the context of the domain of all items $\mathcal{I} \setminus i$, item i is ranked better, if the selected Jaccard correlation coefficient is higher than the ones of the other items or lower analogously.

(v) Public Interest (π_{PubI}): The core aspect of the Public Interest preference is a set of public interest ratings for item i, that is, $\mathcal{P}^i$. A rating $p \in \mathcal{P}^i$ itself is of the form $p = \{x \in \mathbb{Z}_{>0} : x < 6\}$. Calculation of the rank is conducted by building the average among all ratings p of item i and put in the context to the results of the set of items $\mathcal{I} \setminus i$. A higher average rating is ranked better than its lower counterparts. Due to the fact that the Public Interest preference does not rely upon any user specified input, this preference's user specified set of attributes is defined as $\mathcal{L}^{\text{PubI}} = \emptyset$.

(vi) Team (π_{T}): Based on the the empiric results and literature review of the previous chapter 2, the team of an item is considered more successful, if it consists of at least two persons. Building upon the scorecard method, teams fulfilling this constraint are awarded the integer number 1, 0 otherwise. In the context of the set of items $\mathcal{I} \setminus i$, item i is ranked better, if its team size—that is, $|\mathcal{E}^i|$ where $\mathcal{E}^i$ is defined as the set of entrepreneurs forming item i's team —is greater than 1. If so, item i's *boolean* team value is set to *true*, that is, item i is ranked better than other items whose boolean team value is set to *false* (or lower analogously). Due to the fact that the Team preference does not rely upon any user specified input, this preference's user specified set of attributes is defined as $\mathcal{L}^{\text{T}} = \emptyset$.

(vii) Life Cycle (π_{LC}): The input to this preference is a user selected subset of a predefined set of an item's life cycle stages—that is, $\mathcal{L}^{\text{LC}} = \mathcal{C}^u \subset \mathcal{C}$—that are matched against item i's defined life cycle. Matching itself is accomplished by the calculation of the Jaccard correlation coefficient between the set of user specified life cycle stages and item i's actual life cycle stage. In the context of the domain of all items $\mathcal{I} \setminus i$, item i is ranked better, if its calculated Jaccard correlation coefficient is higher than the ones of the other items or lower analogously.

Implementation of the Borda Count In contrast to other collective decision-making methods (such as the plurality rule), the Borda count does not only take the preferred alternative among each agent into account, but rather utilizes all alternatives under the constraint that each agent needs to rank *all* alternatives from most- to least preferred. Each alternative on an agent's ranked list is assigned an integer number, that is, the most preferred alternative is assigned the highest integer n (commonly, the number of alternatives n of the set of alternatives A is either defined as $n = |A|$ or $n = |A| - 1$). Finally, each alternative's merged score is calculated by summation of each individual alternative's scores among all agents. The result is a ranked list of alternatives, exposing preferences among all agents. [Garcia-Lapresta and Martinez-Panero, 2002, p. 167] However, this basic approach requires equality among the importance of agents, thus making this approach only partly applicable to the characteristics of the present work.

In the context of the previously introduced agents, each preference may be seen as an agent and therefore, the amount of agents in the system is equal to the amount of preferences selected by the user. However, the aforementioned original version of the Borda count is not applicable to the present work, due to its constraint on the equality among agents. This implication arises from the fact that each preference's importance may not be equal among other preferences, that is, a user may consider some preferences more important than other preferences. Therefore, the authors propose a *Weighted Borda count* that utilizes all user selected preferences' individually calculated ranked item lists as input and ranks/merges the items based on the selected preferences' weights. The following paragraphs explain this recommendation procedure in great detail.

Once each item $i \in \mathcal{I}^\pi$ is ranked on the basis of a certain preference $\pi \in \Pi$, the next step of the knowledge-based recommender is stated as the process of assigning scores to each item i according to the Borda count.

As already introduced, the Borda count assigns the highest positive Integer, that is, $|\mathcal{I}^\pi|$, to item $i \in \mathcal{I}^\pi$ with the highest rank ρ_{max}. In general, this means that the Borda score of item i is the number of all items (including item i) that are not preferred over i. Furthermore, as introduced previously, there exists the possibility of indifferent items $i \sim_\pi j$—which is also referred to as *ties*—that need to be addressed by the knowledge-based recommender. Therefore, the following equation shows the calculation of a Borda score for an item i among preference π in the domain of a set of items $\mathcal{I}^\pi$:

$$B_{i,\pi,\mathcal{I}^\pi} = |\{j \in \mathcal{I}^\pi : i \lesssim_\pi j\}| \tag{3.36}$$

Subsequently, the Borda count needs to assign scores to each item in $\mathcal{I}^\pi$ and store the *item / value* tuples as ordered pairs of the form

$$\mathcal{I}^\pi_B = \{(i, B_{i,\pi,\mathcal{I}^\pi}) : i \in \mathcal{I}^\pi, B_{i,\pi,\mathcal{I}^\pi} \in \{x \in \mathbb{Z}_{>0} : x \leq |\mathcal{I}^\pi|\}\} \tag{3.37}$$

where $\mathcal{I}^\pi_B$ is stated as the set of ordered *item / borda score* pairs and $B_{i,\pi,\mathcal{I}^\pi}$ is stated as particular Borda score for item i among preference π in the domain of $\mathcal{I}^\pi$.

In the case of ties, the knowledge-based recommender distributes the same Borda score $B_{i,\pi,\mathcal{I}^\pi}$ among all indifferent items of a certain rank. However, as Equation (3.36) specifies, the amount of indifferent items sharing one specific or *tied* rank decreases the available Borda scores. More generically, the procedure of addressing ties in the course of the Borda count is exemplified as follows:

$$B_{x+1} = B_x - \left|\mathcal{I}^{B_x}\right| \tag{3.38}$$

where B_{x+1} is specified as the next (decreasing) Borda score, B_x is stated as the current Borda score and $\mathcal{I}^{B_x} \subset \mathcal{I}^\pi_B$ is defined as the set of items sharing the current Borda score B_x. The reader is referred to Figure 3.3 for an exemplifying illustration on the calculation of Borda scores and the processing of ties in the context of interval B_n (the highest Borda score $|\mathcal{I}^\pi_B| = 255$) and B_1 (the lowest Borda score equal to 1).

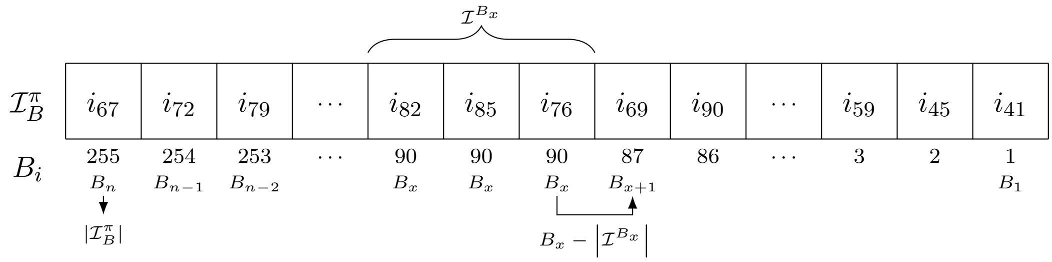

Figure 3.3: Example on the processing of tied Borda scores in the context of the knowledge-based recommender's preference calculation.

Weighted- and Merged Borda Count The final step of knowledge-based recommender in the context of preferences is stated as the calculation of a ranked list of items merged among all user specified preference lists maximizing the user's utility. A user u's selected preferences $\Pi^u \subset \Pi$ are weighted according to a user specified *importance* weighting factor w_π that expresses user u's utility towards a certain preference $\pi \in \Pi^u$. The weights of all user specified weights w_π among $\pi \in \Pi^u$ are summed up to the number 1, that is, $\sum_{\pi \in \Pi^u} w_\pi = 1$. Ultimately, let the merged score of an item $i \in \mathcal{I}$ among the user specified set of preferences Π^u for the domain of items $\mathcal{I}$ be defined as follows:

$$S^{KB}_{i,\Pi,\mathcal{I}^u} = \sum_{\pi \in \Pi^u} B_{i,\pi,\mathcal{I}} \cdot w_\pi \tag{3.39}$$

where $S^{KB}_{i,\Pi^u,\mathcal{I}} \in \mathbb{R}_{>0}$.

The semantics of an item i's score are defined as follows: Let the merged rank be stated as *strict weak order* $<_\Pi$ among the set of preferences Π, then the ranking between two items i and j is defined as follows:

$$i <_\pi j \Leftrightarrow S^{KB}_{i,\Pi,\mathcal{I}} > S^{KB}_{j,\Pi,\mathcal{I}} \tag{3.40}$$

that is, item i expresses a higher utility than item j, if the merged Borda score $S^{KB}_{i,\Pi,\mathcal{I}}$ is higher than $S^{KB}_{j,\Pi,\mathcal{I}}$.

Based on the fact that the knowledge-based recommender does not solely address a single item but is rather applied on a set of items $\mathcal{I}$, the output of the present recommender is stated as a ranked set of items. Therefore, a new data structure needs to be introduced that expresses the rank of an item among a set of other items. More formally, let $\mathcal{I}^{\Pi^u}$ be denoted as a set of ordered pairs $\left(i, S^{KB}_{i,\Pi^u,\mathcal{I}}\right)$, where i is stated as item $i \in \mathcal{I}$ and $S^{KB}_{i,\Pi^u,\mathcal{I}}$ is defined as item i's merged Borda score among all user specified preferences Π^u in the domain of a set of items $\mathcal{I}$. The mathematical notation is specified as follows:

$$\mathcal{I}^{\Pi^u} = \left\{ \left(i, S^{KB}_{i,\Pi^u,\mathcal{I}}\right) : i \in \mathcal{I}, S^{KB}_{i,\Pi^u,\mathcal{I}} \in \mathbb{R}_{>0} \right\} \tag{3.41}$$

whereas—due to illustration purposes—the knowledge-based recommender sorts the calculated set of ordered pairs $\mathcal{I}^{\Pi^u}$ according to $S^{KB}_{i,\Pi^u,\mathcal{I}}$ in descending order, that is, items of the highest utility to the user are shown first.

Sequential Recommendation Process

Finally, it shall be emphasized that in the course of the present work's implementation of the knowledge-based recommender, filters and preferences may be applied independently of each other. However, the following listing of constraints need to be considered:

(i) No filters or preferences selected by the user: In this case, the *whole* set of items $\mathcal{I}$ is returned by the knowledge-based recommender. However, it shall be noted that this particular set of items does not possess a specific order, that is, the logical order specified by the underlying database is considered. As a consequence, the returned set of items is specified as $\mathcal{I}$.

(ii) Only filters selected by the user: This particular case specifies that the *filtered* set of items $\mathcal{I}^{\Phi^u}$ —which depends on a user specified set of filters Φ^u and their corresponding attributes—is returned by the knowledge-based recommender. However, analogously to the case of no selected filters or preferences, this particular set of items does not impose a specific order, that is, the logical order specified by the underlying database is considered. Subsequently, the returned set of items is specified as $\mathcal{I}^{\Phi^u}$.

(iii) Only preferences selected by the user: In contrast to the previous case, the *whole* set of items $\mathcal{I}$ is returned by the knowledge-based recommender. However, this particular set of items is ranked according to the user specified preferences Π^u and their corresponding attributes. Therefore, the returned ranked set of items is specified as $\mathcal{I}^{\Pi^u}$.

(iv) Filters and preferences selected by the user: This specific case utilizes the whole functionality of the knowledge-based recommender. First, the user specified set of filters Φ^u is applied on the whole set of items $\mathcal{I}$ in the course of the present recommender's filtering algorithms. Afterwards, the set of items $\mathcal{I}^{\Phi^u}$ calculated in the previous step is taken as input to the knowledge-based recommender's preference calculation functions that rank this particular set of items according to the user specified preferences Π^u and their corresponding attributes. Subsequently, based on Equation (3.41), let the returned ranked set of items $\mathcal{I}^{\Phi^u\Pi^u}$ in the context of a user specified combination of filters and preferences be mathematically denoted as:

$$
\begin{aligned}
\mathcal{I}^{\Phi^u \Pi^u} &= \bigcup_{i \in \mathcal{I}^{\Phi^u}} \left(i, S^{KB}_{i,\Pi^u,\mathcal{I}^{\Phi^u}}\right) \\
&= \bigcup_{i \in \bigcap_{\phi \in \Phi^u} \phi(\mathcal{I},\mathcal{L}^\phi)} \left(i, \sum_{\pi \in \Pi^u} B_{\pi,i,\mathcal{I}^{\Phi^u}} \cdot w_\pi\right) \\
&= \bigcup_{i \in \bigcap_{\phi \in \Phi^u} \phi(\mathcal{I},\mathcal{L}^\phi)} \left(i, \sum_{\pi \in \Pi^u} \pi(i, \mathcal{L}^\pi, \mathcal{I}^{\Phi^u}) \cdot w_\pi\right)
\end{aligned}
\tag{3.42}
$$

Explanatory example

As of the complexity of the knowledge-based recommender, the following explanatory example visualizes the filters' and preferences' affect on a set of items. Table 3.3 shows this example's set of items:

Table 3.3: Attributes of example items

Attribute	Item a	Item b	Item c	Item d
Products	$\{p_{a_1}, p_{a_2}\}$	$\{p_{b_1}\}$	$\{p_{c_1}, p_{c_2}, p_{c_3}\}$	$\emptyset$
Investments	$\{z_{p_{a_1}}\}$	$\{z_{p_{b_1}}\}$	$\{z_{p_{c_1}}, z_{p_{c_3}}\}$	$\emptyset$
Investment Amount	$z_{p_{a_1}}$: €20000	$z_{p_{b_1}}$: €5000	$z_{p_{c_1}}$: €60000 $z_{p_{c_3}}$: €50000	$\emptyset$
Product Interest	$\{Smartphone, IT\}$	$\{Biology\}$	$\{IT\}$	$\{Food\}$
Date of creation	06.10.2016	24.11.2017	04.04.2015	27.12.2016

Additionally, Table 3.4 shows the user selected filter- and preference settings:

Table 3.4: User selected filter- and preference settings

Filter / Preference	Symbol	$\mathcal{L}^\phi$ / $\mathcal{L}^\pi$	Importance
Investment Range	ϕ_{IR}	$MinAmount = €5000$ $MaxAmount = €55000$	-
Product Interest	π_{ProdI}	$\{IT, Biology, Smartphone\}$	0.8
Date	π_{D}	$\emptyset$	0.3

Due to the fact that one filter and two preferences are selected, the knowledge-based recommender first applies the filters and utilizes the calculated set of items as basis for the ranking according to the preferences. The Investment Amount filter validates whether a certain item fulfils the constraint that there exists at least one investment for at least one product having an investment amount ranging within the interval $MinAmount$ to $MaxAmount$. This constraint holds for the following set of items: $\{a, b, c\}$.

The next step of the knowledge-based recommender is stated as the ranking of the filtered items according to each of the user specified preferences and calculate Borda scores. Finally, the merged Borda score is computed. Table 3.5 illustrates this process:

Table 3.5: Ranking, Borda score and final merged Borda score ranking

Item	π_{ProdI} Ranking		π_{D} Ranking		**Merged Borda score**
	$\rho_{\pi_{\text{ProdI}},i,\mathcal{I}^{\Phi^u}}$	$B_{\pi_{\text{ProdI}},i,\mathcal{I}^{\Phi^u}}$	$\rho_{\pi_{\text{D}},i,\mathcal{I}^{\Phi^u}}$	$B_{\pi_{\text{D}},i,\mathcal{I}^{\Phi^u}}$	$S^{KB}_{i,\Pi^u,\mathcal{I}}$
a	1	3	2	2	$2.\overline{72}$
b	2	2	1	3	$2.\overline{27}$
c	2	2	3	1	$1.\overline{72}$

As may be implied by Table 3.5, the final merged Borda scores for items a, b and c are calculated according to Equation (3.42) as follows:

$$S^{KB}_{a,\Pi^u,\mathcal{I}} = \frac{B_{\pi_{\text{ProdI}},a,\mathcal{I}^{\Phi^u}} \cdot w_{\pi_{\text{ProdI}}} + B_{\pi_{\text{D}},a,\mathcal{I}^{\Phi^u}} \cdot w_{\pi_{\text{D}}}}{w_{\pi_{\text{ProdI}}} + w_{\pi_{\text{D}}}} = \frac{3 \cdot 0.8 + 2 \cdot 0.3}{0.8 + 0.3} = 2.\overline{72}$$
$$S^{KB}_{b,\Pi^u,\mathcal{I}} = \frac{B_{\pi_{\text{ProdI}},b,\mathcal{I}^{\Phi^u}} \cdot w_{\pi_{\text{ProdI}}} + B_{\pi_{\text{D}},b,\mathcal{I}^{\Phi^u}} \cdot w_{\pi_{\text{D}}}}{w_{\pi_{\text{ProdI}}} + w_{\pi_{\text{D}}}} = \frac{2 \cdot 0.8 + 3 \cdot 0.3}{0.8 + 0.3} = 2.\overline{27}$$
$$S^{KB}_{c,\Pi^u,\mathcal{I}} = \frac{B_{\pi_{\text{ProdI}},c,\mathcal{I}^{\Phi^u}} \cdot w_{\pi_{\text{ProdI}}} + B_{\pi_{\text{D}},c,\mathcal{I}^{\Phi^u}} \cdot w_{\pi_{\text{D}}}}{w_{\pi_{\text{ProdI}}} + w_{\pi_{\text{D}}}} = \frac{2 \cdot 0.8 + 1 \cdot 0.3}{0.8 + 0.3} = 1.\overline{72}$$

3.3.5 Social Trust Recommendation

The basic idea of the social recommender associated with the present work is based on the set of trust relationships among users. A user may *follow* another user, that is, the expression of a unidirectional trust relation between the users. As a consequence, information about the fellowship of users highly affects the neighbourhood selection process of the present recommendation algorithm. The social recommender's recommendation algorithm first finds users similar to a target user based on the distribution of the target user's trust. Subsequently, the algorithm calculates the utility of a target item based on the trust relationships between the target user, the peer users and the peer users' rankings of the target item. In fact, the trust relationship modelled in the course of the social recommender may not be regarded a similarity measure but rather be defined as a special kind of neighbourhood selection, that is, a user $u' \neq u$

is included in user u's neighbourhood, if u expresses trust to u'. More formally, let $N_T(u)$ be donated as neighbourhood of user u, where

$$N_T(u) = \{u' \in U \setminus u : u' \in \mathcal{T}^u\} \tag{3.43}$$

and $\mathcal{T}^u \subset \mathcal{U} \setminus u$ is defined as the set of users trusted by user u.

The mathematical notations of the corresponding recommendation algorithms are illustrated as follows:

Trust Likes algorithm (SR^L)

Item recommendations are calculated based on the liked items of the target user's neighbourhood and weighted by item likes of the corresponding peer users. More formally, the social recommender SR^L is specified as follows:

$$S(u,i) = \frac{\sum\limits_{u' \in N_T(u)} r^L(u',i)}{|N_T(u)|} \tag{3.44}$$

where u is defined as the target user, u' is stated as the investigated (peer) user, i is specified as the target item and $N_T(u)$ is defined as the user neighbourhood of user u.

Trust Investments algorithm (SR^I)

Item recommendations are calculated based on the invested items of the target user's neighbourhood and weighted by item investments of the corresponding peer user. More formally, the social recommender SR^I is specified as follows:

$$S(u,i) = \frac{\sum\limits_{u' \in N_T(u)} r^I(u',i)}{|N_T(u)|} \tag{3.45}$$

where u is defined as the target user, u' is stated as the investigated (peer) user, i is specified as the target item and $N_T(u)$ is defined as the user neighbourhood of user u.

Trust Clicks algorithm (SR^C)

Item recommendations are calculated based on the clicked items of the target user's neighbourhood and weighted by item clicks of the corresponding peer user. More formally, the social recommender SR^C is specified as follows:

$$S(u,i) = \frac{\sum\limits_{u' \in N_T(u)} r^C(u',i)}{|N_T(u)|} \tag{3.46}$$

where u is defined as the target user, u' is stated as the investigated (peer) user, i is specified as the target item and $N_T(u)$ is defined as the user neighbourhood of user u.

3.3.6 Hybrid Recommendation

The general concept of the hybrid recommender is stated as a *pipelined cascading* approach based on the target user's item recommendations calculated by the knowledge-based recommender and refined by the knowledge-based item recommendations of all other users in the neighbourhood of the target user. First, the hybrid recommender calculates the similarity between the target user and each of the other users in the neighbourhood on the basis of the item recommendation lists returned by the knowledge-based recommender. The utilized similarity function is based on the *Kendall tau distance*. Based on the calculated similarity scores, the target user's neighbourhood is formed utilizing a certain threshold. Finally, the hybrid recommender calculates the merged score of an item on the basis of its individual *user scores* assigned by the knowledge-based recommender, weighted by the particular user's similarity score and summed up over all users of the neighbourhood. Subsequently, this process is applied to all items of the platform leading to a ranked item recommendation list.

The following approaches introduce the reader to the hybrid recommender's similarity function, the formation of the target user's neighbourhood and, ultimately, the calculation of item recommendations. Due to the fact that some of the following definitions are derived from- and based on the research conducted in the course of the knowledge-based recommender, the reader is referred to subsection 3.3.4 for a detailed elaboration on that matter.

Similarity Function

A similarity function is a measurement that values the similarity between two objects as real number of the interval $[0, 1]$, whereas 1 indicates that the objects of interest are considered to be the same and, analogously, 0 indicates that these objects completely differ from each other. In the context of the hybrid recommender, the objects of interest are defined as the target user u on the one side and a particular peer user $u' \in \mathcal{U} \setminus u$ on the other side. With the aim of calculating the similarity between these two users, the present recommender bases its comparisons on the knowledge-based recommender's final lists of ranked items for each of the users u and u'—that is, $\mathcal{I}^{\Pi^u}$ and $\mathcal{I}^{\Pi^{u'}}$. Therefore, the *distinguishing feature* between the two users is stated as the *internal item rankings* of these two sets. However, until now, the knowledge-based recommender is only applicable on the currently authenticated user of the platform, that is, no user specified data on certain recommendation settings is stored in memory. This circumstance changes in the course of the hybrid recommender.

In order to calculate the similarity between a target user u and another user u' based on their recommendation settings utilized in the course of the knowledge-based recommender—that is, *Filters* and *Preferences*—the hybrid recommender utilizes a *user-based recommendation profile* that stores these settings in memory (the reader is referred to the present chapter's model subsection 3.3.1 for a detailed representation of the profile's attributes). However, due to the pipelined cascading hybrid's requirement on a *finalized* set of items to elaborate upon, that is, in the course of the hybrid recommender, no items may be removed or added between each calculation iteration, only the Preference settings are stored in each user's recommendation profile. As a consequence, the set of items needed for the calculation of user similarity and the computation of recommendations, is defined as the whole set of items held by the platform—that is, $\mathcal{I}$. In order to calculate the similarity between two users based on the mentioned constraints, a similarity function capable of identifying and measuring the differences between the rankings of two item lists is needed.

One possible candidate fitting to the present modelling constraints is stated as the *Kendall tau distance* (the reader is referred to the background subsection 3.1.3 for a detailed representation and the calculation of the Kendall tau distance), which calculates the distance between two ranked lists based on their number of discordant pairs, that is, the number of pairs having a different order among the lists. However, the original implementation does not consider the existence of ties, that is, items of the same rank between each of the lists. In order to solve this issue, the present implementation of the Kendall tau distance does not solely take the rank of an item in each list into account, but rather utilizes the score $S^{KB}_{i,\Pi^u,\mathcal{I}}$ calculated by the knowledge-based recommender for item $i \in \mathcal{I}$ in the context of user u's predefined recommendation settings. The plausibility of this approach is backed by the final score calculations of the knowledge-based recommender, which rely on weighting factors that sum up to the integer 1. This design decision leads to the fact that the calculated ranks increase or decrease *linearly* and share a maximum rank defined as $|\mathcal{I}|$. Therefore, these lists of ranked items are considered comparable as long as both of them contain the same items. Subsequently, a tie between the knowledge-based recommender's scores $S^{KB}_{i,\Pi^u,\mathcal{I}}$ and $S^{KB}_{i,\Pi^{u'},\mathcal{I}}$ of users u and u' for item $i \in \mathcal{I}$ emerges, if $S^{KB}_{i,\Pi^u,\mathcal{I}} = S^{KB}_{i,\Pi^{u'},\mathcal{I}}$ holds. However, the scenario of ties needs to be considered in the calculation of the similarity measure as well, in order to be addressed properly.

Kendall tau is defined as distance between two ranked lists or rankings. A ranking for a user u is represented as ρ^u, that is, each item i possesses an assigned rank ρ^u_i, whereas a high rank expresses that item i is of high utility in the context of the target user u (low utility analogously). Consequently, a discordant pair is defined as follows: Let (i, j) be denoted as discordant pair between two lists ρ^u and $\rho^{u'}$ of users u and u', if one of the following conditions holds:

$$\begin{aligned}
&\rho^u_i < \rho^u_j \wedge \rho^{u'}_i > \rho^{u'}_j \\
&\rho^u_i > \rho^u_j \wedge \rho^{u'}_i < \rho^{u'}_j \\
&\rho^u_i = \rho^u_j \wedge \rho^{u'}_i \neq \rho^{u'}_j \\
&\rho^u_i \neq \rho^u_j \wedge \rho^{u'}_i = \rho^{u'}_j
\end{aligned} \tag{3.47}$$

Subsequently, the calculation of the Kendall tau distance is conducted by computing the number of discordant item pairs between two lists, normalized by the total number of list items $|\rho^u| = |\rho^{u'}|$, more formally:

$$\mathcal{K}(\rho^u, \rho^{u'}) = \frac{n_d}{n \cdot (n-1)/2} \tag{3.48}$$

where ρ^u and $\rho^{u'}$ are stated as user u's- and user u''s list of ranked items calculated by the knowledge-base recommender utilizing the users' individual Preference settings, n_d is defined as the number of discordant pairs between ρ^u and $\rho^{u'}$ and $n = |\rho^u| = |\rho^{u'}| = |\mathcal{I}|$ is specified as the size of each list.

Finally, in order to utilize the Kendall tau distance as similarity measure between two users u and u', $\mathcal{K}(\rho^u, \rho^{u'})$ needs to be subtracted from 1, more formally: art

$$k_{u,u'} = sim_H(u, u') = 1 - \mathcal{K}(\rho^u, \rho^{u'}) = 1 - \frac{n_d}{n \cdot (n-1)/2} \tag{3.49}$$

As of the complexity of the presented similarity measure, the following explanatory example visualizes the calculation of the similarity between two users u and u' utilizing the Kendall tau similarity measure. Table 3.6 shows this example's set of items combined with the user-based rank calculated by the knowledge-based recommender.

Table 3.6: User rankings per item

Rankings per user	Item a	Item b	Item c	Item d
ρ^u	4	3	3	1
$\rho^{u'}$	2	3	4	1

The first step of calculating the similarity between user u and u' is stated as determining the discordant pairs between the users' lists of rankings. The reader is referred to Table 3.7 for an illustration on this calculation process.

Table 3.7: Calculation of discordant pairs

Pair	ρ_i^u vs. ρ_j^u	$\rho_i^{u'}$ vs. $\rho_j^{u'}$	Count (n_d)
(a, b)	$4 > 3$	$2 < 3$	$\times$
(a, c)	$4 > 3$	$2 < 4$	$\times$
(a, d)	$4 > 1$	$2 > 1$	
(b, c)	$3 = 3$	$3 < 4$	$\times$
(b, d)	$3 > 1$	$3 > 1$	
(c, d)	$3 > 1$	$4 > 1$	

Finally, the calculation of the similarity score $k_{u,u'}$between user u and u' is conducted by the utilization of $\mathcal{K}(\rho^u, \rho^{u'})$ and accomplished as follows:

$$k_{u,u'} = sim_H(u, u') = 1 - \mathcal{K}(\rho^u, \rho^{u'}) = 1 - \frac{n_d}{n \cdot (n-1)/2} = 1 - \frac{3}{4 \cdot (4-1)/2} = 0.5$$

Neighbourhood Formation

With the aim of improving recommendation quality and reducing calculational overhead, the hybrid recommender implements a neighbourhood function $N_H(u)$ that reduces the set of peer users taken as input to the recommendation algorithm. The neighbourhood function itself is based on a threshold that a peer user's similarity score needs to reach or surpass in order for the peer user to be included into the neighbourhood.

Nevertheless, Jannach et al. [2010, pp. 17–18] state that choosing the appropriate threshold is a non-trivial task. If the threshold is set too high, the coverage is reduced considerably. In contrast, if the threshold is chosen too low, the size of the neighbourhood is only pa

rtially reduced (the reader is referred to the background subsection 3.1.3 for a detailed discussion on neighbourhood formation). However, research of the present work's chapter 2 indicates that the future ratings sets and the amount of users held by the platform is stated as being considerably low. Due to these reasons, the threshold is set to the real number 0.7. More formally, the neighbourhood of the hybrid recommender's recommendation algorithm is formed as follows:

$$N_H(u) = \{u' \in U \setminus u : sim_H(u, u') \geq 0.7\} \tag{3.50}$$

Hybrid Recommendation Algorithm (S^H)

The hybrid recommender's final step is stated as the calculation of a ranked list of items merged among the peer users' recommendation settings maximizing the target user's utility. In order to calculate the hybrid recommender's final rank for an item i in the context of the target user u, each peer user $u' \in N_H(u)$'s knowledge-based recommender's score $S^{KB}_{i,\Pi^{u'},\mathcal{I}}$ is weighted by u''s similarity score $k_{u,u'}$ and averaged on the basis of $|N_H(u)|$. Ultimately, let the hybrid recommender's score of an item $i \in \mathcal{I}$ be defined as follows:

$$S^H_{i,u,N_H(u),\mathcal{I}} = \sum_{u' \in N_H(u)} \frac{k_{u,u'} \cdot S^{KB}_{i,\Pi^{u'},\mathcal{I}}}{|N_H(u)|} \tag{3.51}$$

where $S^H_{i,u,N_H(u),\mathcal{I}} \in \mathbb{R}_{>0}$.

The semantics of an item i's score are defined as follows: Let the hybrid recommender's rank be stated as *strict weak order* $<_{S^H}$ among the set of items $\mathcal{I}$, then the ranking between two items i and j is defined as follows:

$$i <_{S^H} j \Leftrightarrow S^H_{i,u,N_H(u),\mathcal{I}} > S^H_{j,u,N_H(u),\mathcal{I}} \tag{3.52}$$

that is, item i expresses a higher utility than item j, if the hybrid recommender's score $S^H_{i,u,N_H(u)}$ is higher than $S^H_{j,u,N_H(u)}$.

Based on the fact that the hybrid recommender does not solely address a single item but is rather applied on a set of items $\mathcal{I}$, the output of the present recommender is stated as a ranked set of items. Therefore, a new data structure needs to be introduced that expresses the rank of an item among a set of other items. More formally, let $\mathcal{H}^{u,N_H(u),\mathcal{I}}$ be denoted as a set of ordered pairs $(i, S^H_{i,u,N_H(u),\mathcal{I}})$, where i is stated as item $i \in \mathcal{I}$ and $S^H_{i,u,N_H(u),\mathcal{I}}$ is defined as item i's hybrid recommender's score among user u and its neighbourhood $N_H(u)$ in the domain of all items $\mathcal{I}$. Finally, the mathematical notation is specified as follows:

$$\mathcal{H}^{u,N_H(u),\mathcal{I}} = \left\{ \left(i, S^H_{i,u,N_H(u),\mathcal{I}} \right) : i \in \mathcal{I}, S^H_{i,u,N_H(u),\mathcal{I}} \in \mathbb{R}_{>0} \right\} \tag{3.53}$$

whereas—due to illustration purposes—the hybrid recommender sorts the calculated set of ordered pairs $\mathcal{H}^{u,N_H(u),\mathcal{I}}$ according to $S^H_{i,u,N_H(u),\mathcal{I}}$ in descending order, that is, items of the highest utility to the target user u are shown first.

3.3.7 Recommender System Prototype

The main purpose of the proposed recommendation system's software prototype is to provide a personalized recommendation experience to the user of the system. Therefore, all mathematically designed recommendation algorithms are implemented in a *parallelized* approach, that is, each of these recommenders are separately applicable by the user. It has been decided that no constraints on whether one particular recommendation algorithm shall be preferred over another or whether various algorithms shall be combined in order to enhance the likelihood of improving the user's satisfaction, need to be fulfilled. These considerations are being elaborated in the recommender system's evaluation specialization topic, which is not part of the present work. Figure 3.4 illustrates the parallelized recommendation architecture of the recommender system prototype.

One major design choice of implementing the recommendation system's software prototype is stated as the adaptation of a *plugin-based software architecture* that allows for dynamic extensions of the recommendation system (such as inclusion of new recommendation algorithms). Therefore and due to performance aspects in terms of computational calculation, the prototype's *recommendation engine* and the *user interface* are separated into two components implemented as independent pieces of software. While the recommendation engine is developed utilizing the *Java*[2] programming language, *Angular*[3] is chosen for crafting the web-based user interface. The communication between both components is accomplished by the utilization of RESTful[4] WEB services.

Finally, backed by the research conducted in the course of the previous chapter 2 and nowadays' zeitgeist, one of the core principles utilized for developing the web-based user interface is stated as *responsive design*, that is, a user interface that actively adapts to the platform it is consumed on (such as mobile devices or desktop computers). The reader is referred to Figures 3.5 and 3.6 for a visual representation of a user's desktop- and an item's mobile view.

[2]Java programming language: https://java.com/de/download/
[3]Angular web application platform: https://angular.io/
[4]Z. Shelby [2012]. *Constrained RESTful Environments (CoRE) Link Format.* RFC 6690. RFC Editor, pp. 1–22.

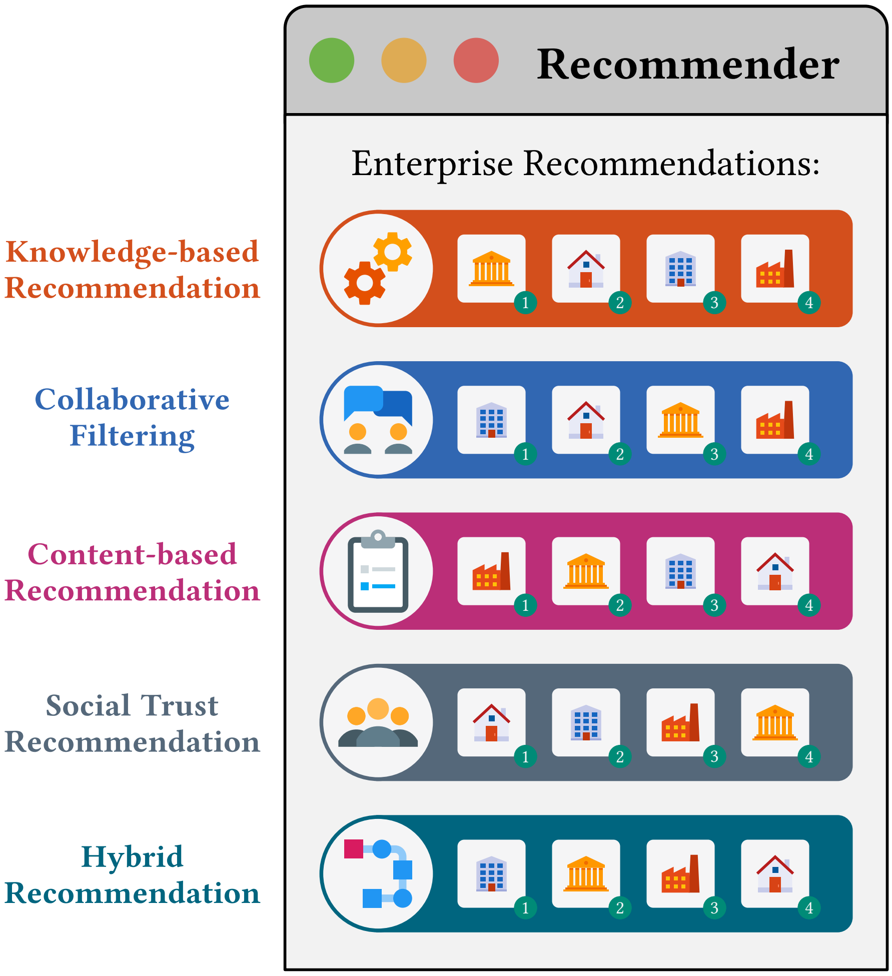

Figure 3.4: General architecture of the recommender system prototype based on parallelized types of recommenders.

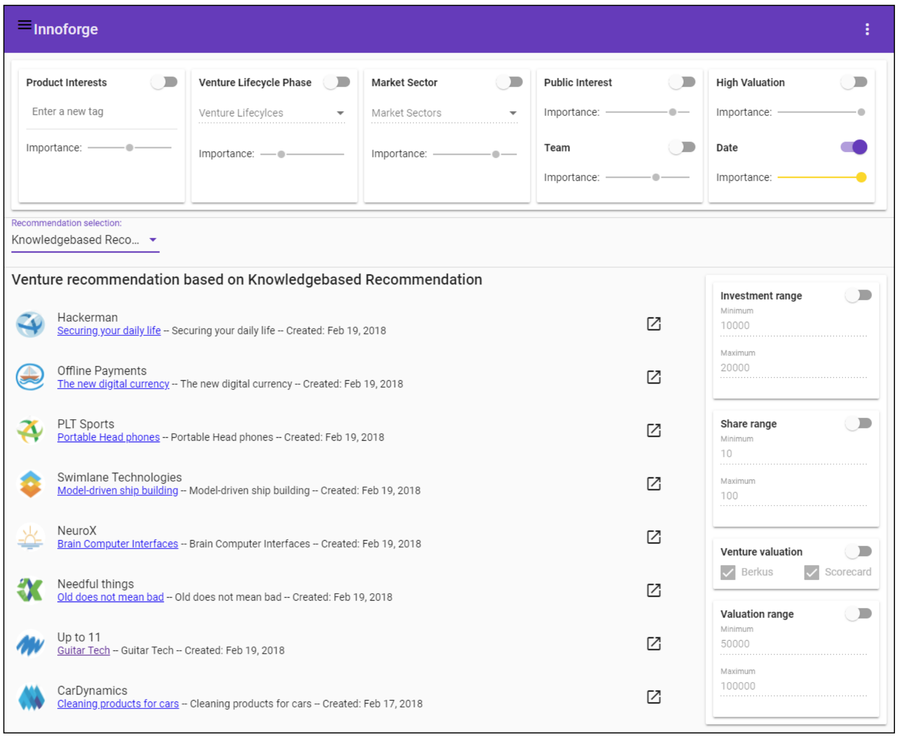

Figure 3.5: The user view of the recommender system prototype (Preferences & Filters).

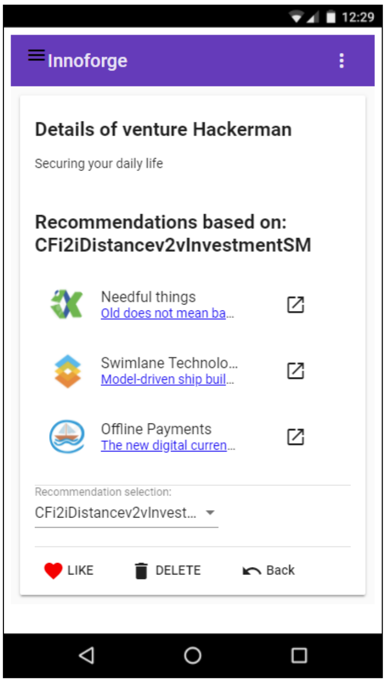

Figure 3.6: Responsive illustration of the recommender system's prototype's item view.

3.4 Answers to the Research Questions

The objective of this section lies in the discussion of the present chapter's research questions (the reader is referred to subsection 3.2.1 of the methodology section) on the basis of the obtained results.

Which recommendation algorithms and -techniques shall be considered in a computational recommendation system in the domain of early-stage enterprise investment, in order to guarantee highly personalized recommendations for investors?

Research conducted in the course of the present work's previous chapter 2 *Investment Decision-making & Venture Valuation* indicates many different use cases a potential recommender system in the mentioned domain needs to address. The crucial aspects of these findings include but are not limited to personalized recommendation of items in the course of other users' rating behaviour, viewing the most interesting items based on a user's personal preferences, exploring items that are similar to items the user interacted with in the past and expressing trust among other users. Independently, all of these use cases share the concept of personalization in its own individual way. With the aim of addressing these personalization concepts, the present work's recommender system unites multiple types of recommendation algorithms that, ultimately, address all of the mentioned use cases. These algorithms include the following recommendation techniques: Collabortive filtering, content-based-, knowledge-based, social- and hybrid recommendation.

How can the cold start problem in the context of computational recommendation systems in the domain of early-stage enterprise investment, be addressed?

The cold start problem in the domain of recommendation systems arises if there is not enough or no ratings data for items available. Subsequently, recommendation architectures that build their recommendations on ratings data are not applicable any longer (such as collaborative filtering techniques). Especially the domain of early-stage enterprise investment faces this circumstance, for it is this domain's users who share the characteristics of *one time buyers*, that is, users who do not intend to buy items on a frequent basis. In order to overcome this issue, the present work implements a knowledge-based recommender that does not rely on ratings data and therefore enables the user to utilize the recommendation system even if there is not sufficient ratings data available.

Which constraints does a software prototype of the computational recommendation system need to fulfil, in order to guarantee technical- and algorithmic feasibility

Monolithic sofware architectures generally face the problem of hardly scalable resources due to the chosen system architecture. Nowadays' recommender systems show that their domains of application generate considerably large amounts of data that needs to be processed in a considerably short amount of time. Due to these reasons, the software architecture of the present work's software prototype was designed highly scalable on the basis of a micro services architecture. One of the constraints of this approach is stated as the split of the recommendation engine and the user interface enabling independent scaling of each of these components if needed. Independently of the recommender system's performance in terms of computational calculation speed, today's zeitgeist shows that a revolution in human computer interfaces changed the way users interact with the digital world. However, as revolutionary as these changes might be, in a time that is mainly characterized by the efficiency of processes, it is these very changes in human computer interaction—the children of this revolution—users are not capable of reviving from: Mobile devices. In order to address this circumstance, the user interface of the recommendation system is developed utilizing responsive design functionality that actively adapts to the platform it is consumed on (such as mobile devices or desktop computers).

Conclusion

The purpose of the present chapter *Recommender Systems for Early-Stage Enterprise Investment* was to conceptualize a recommender system in the domain of early-stage enterprise investment based on the findings of co-author Christian Ohrfandl's specialization topic *Investment Decision-making & Venture Valuation*. The crucial aspects of these findings include but are not limited to personalized recommendation of items in the course of other users' rating behaviour, viewing the most interesting items based on a user's personal recommendation settings, exploring items that are similar to items the user interacted with in the past and expressing trust among other users. Based on these constraints, a recommender system was modelled that unites the following set of recommenders: *Collaborative filtering*, *content-based-*, *knowledge-based-*, *social-* and *hybrid* recommendation algorithms. Finally, the conceptual model of this very recommender system has been implemented as a highly scalable, plugin-based software prototype that might be easily extended by different recommendation algorithms in the course of future research.

To the authors' best knowledge, very few publications are available in the literature that combine the domain of early-stage enterprise investment with the domain of recommender systems. Therefore, this thesis's present chapter may not only be seen as modest contribution to the scientific research domain of recommender systems, but also be valued as novel approach to objectively transform investors' rules of thumb or gut feelings into transparent decision-making processes utilized in the course of a recommendation system. In particular, the utilized comprehensive approach, that is, the inclusion of a wide range of recommenders with the aim of maximizing the user's utility independently of the use case, enables the collection of various amounts of meta data that may be taken as basis for future research. Nevertheless, there are certain factors limiting the present research.

A limitation of the present work may be seen in the fact that the design choices the present recommender is implemented upon were not evaluated in the course of the present chapter. Therefore, the authors are not able to make any significant statements on the verification of the overall recommendation quality in terms of user satisfaction. Additionally, the selected and implemented types of recommendation algorithms are based on- and therefore also limited to the research findings of the previous chapter 2. However, the outcomes of the present work generate a wide range of future research possibilities.

One of the most interesting opportunities for future research arises from the data obtained after users' frequent use of the platform. The gathered data may be further analysed in order to gain insights on potential relationships among quantifiable user behaviour or may even lead to the finding of generally valid success factors of early-stage enterprises. Independently, additional research may address the mentioned limitations of the present work. In particular, qualitative- or quantitative evaluations of recommendation quality in terms of user satisfaction may answer the question, whether the implemented design decisions improve a user's utility when using the system. In fact, it is precisely this very evaluation that is researched by co-author Johannes Luef in the course of his specialization topic *User-centred Evaluation*.

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Appendices

APPENDIX A

Qualitative Questionnaire Data

Qualitative Questionnaire Questions

Table A.1: Questions of the qualitative questionnaire

Idx	Category	Type	Question
Q1	Characteristics of Investors	Dichotomous (Binary; Yes/No)	Have you already invested in an early-stage enterprise?
Q2	Characteristics of Investors	Open	Which maturity level (enterprise life-cycle) do you prefer for investments?
Q3	Characteristics of Investors	Open	How do you decide on the investment in a venture?
Q4	Characteristics of Investors	Open	Business Plan evaluation: Which criteria is important? Which factors determine, whether to conduct an investment into an early-stage enterprise?
Q5	Characteristics of Investors	Open	A business plan is de facto a self-expression of an early-stage enterprise. Shall an investor trust these statements? Substantiate your answer, please.

To be continued on next page…

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Q6	Characteristics of Investors	Open	What does the term 'risk awareness' mean to you?
Q7	Characteristics of Investors	Likert (1...5, less risky...very risky)	Which risk category would you rate yourself?
Q8	Characteristics of Investors	Open	How important would you assess 'networks' or 'networking' for early-stage enterprises respectively? Would you provide 'networks' as intangible assets in the course of an investment? If so, how would you assess its worth compared to monetary assets?
Q9	Characteristics of Investors	Open	How do you think about a possibility to know the various courses of an investment in advance? For instance, predefinition of various progress evolutions in advance to the actual investment?
Q10	Characteristics of Investors	Open	How do historic investment decisions influence a new investment? Do you pursue an investment portfolio?
Q11	Characteristics of Investors	Open	Do you rely on the opinions of other investors for investment decision-making processes?
Q12	Venture Valuation	Open	How can the success of an early-stage enterprise be measured? What indicators exist that show the success of an early-stage enterprise?
Q13	Venture Valuation	Open	Which key performance indicators for the valuation of early-stage enterprises do you trust?
Q14	Venture Valuation	Open	Which venture valuation methods do you know?
Q15	Venture Valuation	Multiple Choice	Do you know the following venture valuation methods?
Q16	Venture Valuation	Open	How do you think about traditional venture valuation methods such as the Discounted Cash Flow (DCF) method?

To be continued on next page...

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Q17	Venture Valuation	Open	Which additional venture valuation methods do you use (for instance, which rules of thumb?)?
Q18	Venture Valuation	Dichotomous (Binary; Yes/No)	If you mentioned additional methods: Do you think that these methods are meaningful or accurate when applied on early-stage enterprises?
Q19	Venture Valuation	Dichotomous (Binary; Yes/No)	Do you use venture valuation methods that especially apply to the valuation of early-stage enterprises?
Q20S1	Venture Valuation	Open	Which methods do you use?
Q20S2	Venture Valuation	Open	How would you rate usefulness of these methods? Do you assess these methods advantageous especially when considering the valuation of early-stage enterprises?
Q21	Venture Valuation	Dichotomous (Binary; Yes/No)	Do you know the 'Real Options Approach'?
Q22aS1	Venture Valuation	Open	Real Options Approach: How do you think about this venture valuation method, after reading it's description?
Q22aS2	Venture Valuation	Dichotomous (Binary; Yes/No)	Real Options Approach: Would you use this method?
Q22bS1	Venture Valuation	Open	Real Options Approach: How do you think about this venture valuation method?
Q22bS2	Venture Valuation	Dichotomous (Binary; Yes/No)	Real Options Approach: Would you use this method?
Q23	Venture Valuation	Open	How would you approach the valuation of early-stage enterprises?
Q24	Venture Valuation	Open	Why and when are industry sector dependent valuation key performance indicators required?

To be continued on next page…

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Q25	Characteristics of early-stage enterprises	Open	Which characteristics of early-stage enterprises are important to you?
Q26	Characteristics of early-stage enterprises	Likert (1...5, unimportant...very important)	Which characteristics does an early-stage enterprise and its environment exhibit in order for you to conduct an investment? Assign the characteristics according to it's importance.
Q27	Characteristics of early-stage enterprises	Open	Which characteristics of the business plan are most important to you?
Q28	Characteristics of early-stage enterprises	Open	Why are the mentioned characteristics important?
Q29	Characteristics of early-stage enterprises	Open	Which factors indicate whether an early-stage enterprise shall be invested in?
Q30	Characteristics of early-stage enterprises	Open	How do you decide upon investing in an early-stage enterprise? Which constraints need to at least be fulfilled in order for you to consider investing?
Q31	Characteristics of early-stage enterprises	Open	Under which conditions would you decline investing in an early-stage enterprise? Which reasons can you think of?
Q32	Recommender System (Platform)	Open	Which characteristics would a platform for a recommendation of early-stage enterprises to investors exhibit, in order to offer added value to you?
Q33	Recommender System (Platform)	Open	Which requirements would you place onto such a platform?
Q34	Recommender System (Platform)	Open	Which problems would you assess when thinking of the development of such a platform?

To be continued on next page...

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Q35	Recommender System (Platform)	Open	Under which conditions / assumptions could such a platform for the recommendation of early-stage enterprises to investors exist?
Q36	Recommender System (Platform)	Open	Think about the factor '(In)security of an investment': How could this factor be modelled in such platform and communicated to potential users?
Q37	Recommender System (Platform)	Open	Under which criteria (input variables) can a 'matching' between early-stage enterprises and investors be accomplished? Are such variables generally transferable to other early-stage enterprises?

APPENDIX B

Quantitative Questionnaire Data

B.1 Question 1: Based on which criteria do you decide upon, whether an investment in an early-stage enterprise shall be conducted?

Dataset (Likert, ordinal scale 1-5 incl. no specification [NA])

Table B.1: Question 1: dataset (q1q3data.csv)

Participant	SQ1	SQ2	SQ3	SQ4	SQ5	SQ6	SQ7	SQ8	SQ9	SQ10	Q3
p1	4	4	2	5	4	4	5	3	4	4	Yes
p2	4	5	2	4	5	5	5	4	2	4	Yes
p3	5	2	2	3	4	4	2	2	1	3	Yes
p4	3	2	2	5	4	4	3	5	2	5	Yes
p5	2	3	1	5	3	5	5	5	4	3	Yes
p6	3	2	4	3	4	5	4	4	2	4	Yes
p7	4	NA	NA	5	4	5	4	4	4	5	NA
p8	5	3	2	4	3	4	2	4	2	2	NA
p9	3	3	2	4	5	5	5	5	3	4	Yes
p10	3	3	4	4	5	3	4	2	2	3	No
p11	3	2	3	1	2	2	2	3	1	1	Yes
p12	3	3	NA	5	4	3	3	3	1	3	Yes
p13	5	4	3	4	5	4	3	3	4	4	NA
p14	2	3	1	2	4	4	2	3	3	4	Yes

To be continued on next page…

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p15	4	3	5	5	3	4	2	1	4	1	Yes
p16	4	3	5	3	4	5	5	4	5	2	No
p17	3	4	2	4	5	NA	4	NA	5	4	No
p18	3	2	5	5	5	5	5	5	4	5	Yes
p19	4	4	3	5	5	4	4	3	2	4	Yes
p20	3	2	3	4	3	3	4	3	3	4	No
p21	5	1	1	3	5	5	5	3	4	5	NA
p22	3	3	3	4	5	4	4	4	1	5	No
p23	5	4	4	3	4	3	2	3	3	3	Yes
p24	4	3	2	4	5	5	4	5	3	4	No
p25	2	3	5	4	3	4	4	2	4	2	No

Setup (R dataset)

```
# Read data from CSV
data <- read.csv("q1q3data.csv", row.names=1)

# Show internal structure of the data
str(data, list.len=ncol(data), vec.len=nrow(data))
'data.frame':         25 obs. of  11 variables:
 $ Q1Sub1 : int  4 4 5 3 2 3 4 5 3 3 3 3 5 2 4 4 3 3 4 3 5 3 5 4 2
 $ Q1Sub2 : int  4 5 2 2 3 2 NA 3 3 3 2 3 4 3 3 3 4 2 4 2 1 3 4 3 3
 $ Q1Sub3 : int  2 2 2 2 1 4 NA 2 2 4 3 NA 3 1 5 5 2 5 3 3 1 3 4 2 5
 $ Q1Sub4 : int  5 4 3 5 5 3 5 4 4 4 1 5 4 2 5 3 4 5 5 4 3 4 3 4 4
 $ Q1Sub5 : int  4 5 4 4 3 4 4 3 5 5 2 4 5 4 3 4 5 5 5 3 5 5 4 5 3
 $ Q1Sub6 : int  4 5 4 4 5 5 5 4 5 3 2 3 4 4 4 5 NA 5 4 3 5 4 3 5 4
 $ Q1Sub7 : int  5 5 2 3 5 4 4 2 5 4 2 3 3 2 2 5 4 5 4 4 5 4 2 4 4
 $ Q1Sub8 : int  3 4 2 5 5 4 4 4 5 2 3 3 3 3 1 4 NA 5 3 3 3 4 3 5 2
 $ Q1Sub9 : int  4 2 1 2 4 2 4 2 3 2 1 1 4 3 4 5 5 4 2 3 4 1 3 3 4
 $ Q1Sub10: int  4 4 3 5 3 4 5 2 4 3 1 3 4 4 1 2 4 5 4 4 5 5 3 4 2
 $ Q3     : Factor w/ 2 levels "No","Yes": 2 2 2 2 2 2 NA NA 2 1 2 2
  ↪  NA 2 2 1 1 2 2 1 NA 1 2 1 1
```

Listing 1: Question 1 – Setup (R dataset)

Descriptive Statistics

```
# Print LaTeX table with descriptive statistics
stargazer::stargazer(data, summary.stat = c("n", "mean", "sd", "min",
 ↪  "p25", "median", "p75", "max"))

# Print more detailed descriptive statistics (grouped by Q3; LaTeX
 ↪  table format)
data$Q3 <- factor(data$Q3, levels = c("Yes", "No"))
```

```

cat(paste("SQ", " & ",
          "Group", " & ",
          "N", " & ",
          "N (valid)", " & ",
          "Mean", " & ",
          "Std. Dev.", " & ",
          "Min", " & ",
          "Pctl(25)", " & ",
          "Median", " & ",
          "Pctl(75)", " & ",
          "Max",
          sep = ""
    ), sep = "\n"
)
cat("-----------------------------------------------------------------------------------", sep = "\n")

for (i in 1:(ncol(data)-1)) {
  statistics <- FSA::Summarize(data[[i]], digits=3, na.rm = TRUE, nvalid = "always", percZero = "always")
  statisticsGrouped <- FSA::Summarize(data[[i]] ~ data$Q3, digits=3, na.rm = TRUE, nvalid = "always", percZero = "always")

  sqindex <- paste("SQ", i, sep = "")

  cat(paste(sqindex, " & ",
            "Overall", " & ",
            statistics[[1]], " & ",
            statistics[[2]], " & ",
            statistics[[3]], " & ",
            statistics[[4]], " & ",
            statistics[[5]], " & ",
            statistics[[6]], " & ",
            statistics[[7]], " & ",
            statistics[[8]], " & ",
            statistics[[9]], "\\\\",
            sep=""),
      sep = "\n"
  )

  ws <- ""

  for (z in 1:nchar(sqindex)) {
    ws <- paste(ws, " ", sep = "")
  }

  for (j in 1:length(statisticsGrouped$data$Q3)) {
    cat(paste(ws, " & ",
              statisticsGrouped$data$Q3[[j]], " & ",
              statisticsGrouped$n[[j]], " & ",
              statisticsGrouped$nvalid[[j]], " & ",
```

```
                statisticsGrouped$mean[[j]], " & ",
                statisticsGrouped$sd[[j]], " & ",
                statisticsGrouped$min[[j]], " & ",
                statisticsGrouped$Q1[[j]], " & ",
                statisticsGrouped$median[[j]], " & ",
                statisticsGrouped$Q3[[j]], " & ",
                statisticsGrouped$max[[j]], "\\\\",
                sep=""),
          sep = "\n"
      )
    }

  cat(paste(ws, "\\hline"), sep = "\n")
}
```

Listing 2: Question 1 – Descriptive Statistics

Test for Normality

```
# Test each sub likert item of the question for normality
for(i in 1:(ncol(data)-1)) {
    print(shapiro.test(data[[i]]))
}

        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.87691, p-value = 0.005971


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.90525, p-value = 0.02785


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.88947, p-value = 0.01544


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.8455, p-value = 0.001449


        Shapiro-Wilk normality test

data:  data[[i]]
```

```
W = 0.83136, p-value = 0.0007957


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.83245, p-value = 0.001051


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.83415, p-value = 0.0008941


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.90714, p-value = 0.03059


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.90333, p-value = 0.0217


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.88283, p-value = 0.007909
```

Listing 3: Question 1 – Test for Normality

Test for Reliability (Cronbach Alpha)

```
# Run the alpha test only for columns data likert columns (i.e.
↪  without column Q3)
psych::alpha(data[, c(1:(ncol(data) - 1))])

Some items ( Q1Sub1 Q1Sub3 ) were negatively correlated with the
↪  total scale and
probably should be reversed.
To do this, run the function again with the 'check.keys=TRUE' option
Reliability analysis
Call: psych::alpha(x = data[, c(1:(ncol(data) - 1))])

  raw_alpha std.alpha G6(smc) average_r S/N  ase mean   sd
      0.63      0.66     0.79      0.16   2 0.11  3.5 0.53

 lower alpha upper     95% confidence boundaries
```

```
0.43 0.63 0.84

 Reliability if an item is dropped:
        raw_alpha std.alpha G6(smc) average_r S/N alpha se
Q1Sub1       0.67      0.70    0.81      0.21 2.4    0.097
Q1Sub2       0.64      0.67    0.78      0.18 2.0    0.107
Q1Sub3       0.72      0.73    0.82      0.23 2.7    0.081
Q1Sub4       0.58      0.62    0.76      0.15 1.6    0.123
Q1Sub5       0.56      0.58    0.70      0.14 1.4    0.128
Q1Sub6       0.55      0.57    0.72      0.13 1.3    0.133
Q1Sub7       0.53      0.58    0.73      0.13 1.4    0.140
Q1Sub8       0.61      0.64    0.77      0.16 1.8    0.116
Q1Sub9       0.60      0.63    0.77      0.16 1.7    0.118
Q1Sub10      0.58      0.61    0.71      0.15 1.6    0.123

 Item statistics
         n raw.r std.r  r.cor r.drop mean   sd
Q1Sub1  25 0.155 0.186  0.039 -0.036  3.6 0.96
Q1Sub2  24 0.333 0.358  0.262  0.158  3.0 0.91
Q1Sub3  23 0.089 0.029 -0.116 -0.167  2.9 1.32
Q1Sub4  25 0.599 0.589  0.508  0.440  3.9 1.04
Q1Sub5  25 0.657 0.710  0.733  0.570  4.1 0.88
Q1Sub6  24 0.743 0.755  0.765  0.655  4.1 0.85
Q1Sub7  25 0.725 0.727  0.722  0.617  3.7 1.14
Q1Sub8  24 0.494 0.497  0.447  0.306  3.5 1.10
Q1Sub9  25 0.558 0.525  0.456  0.359  2.9 1.26
Q1Sub10 25 0.608 0.605  0.619  0.411  3.5 1.19

Non missing response frequency for each item
           1    2    3    4    5 miss
Q1Sub1  0.00 0.12 0.40 0.28 0.20 0.00
Q1Sub2  0.04 0.25 0.46 0.21 0.04 0.04
Q1Sub3  0.13 0.35 0.22 0.13 0.17 0.08
Q1Sub4  0.04 0.04 0.20 0.40 0.32 0.00
Q1Sub5  0.00 0.04 0.20 0.36 0.40 0.00
Q1Sub6  0.00 0.04 0.17 0.42 0.38 0.04
Q1Sub7  0.00 0.24 0.12 0.36 0.28 0.00
Q1Sub8  0.04 0.12 0.38 0.25 0.21 0.04
Q1Sub9  0.16 0.24 0.20 0.32 0.08 0.00
Q1Sub10 0.08 0.12 0.20 0.40 0.20 0.00
Warning message:
In psych::alpha(data[, c(1:(ncol(data) - 1))]) :
  Some items were negatively correlated with the total scale and probably
should be reversed.
To do this, run the function again with the 'check.keys=TRUE' option
```

Listing 4: Question 1 – Test for Reliability (Cronbach Alpha)

Likert Statistics

```
# Load grid library needed for likert processing (at least in case of a Linux system)
library(grid)

# Define levels
levels = c("Unimportant", "Rather unimportant", "Neutral", "Rather important", "Important")

# Copy data
dataLikert <- data

# Rename responds
for(i in 1:(ncol(dataLikert)-1)) {
  dataLikert[[i]] = likert::recode(dataLikert[[i]], from=c(1, 2, 3, 4, 5), to=levels)
}

# Replace columns with an ordered factor
for(i in 1:(ncol(dataLikert)-1)) {
  dataLikert[[i]] = factor(dataLikert[[i]], levels = levels, ordered = TRUE)
}

# Rename columns
cols = c(
  "Recommendations (e.g. by investors)",
  "Historic investment decisions",
  "Relationship to entrepreneur(s)",
  "Industry sector",
  "Experience of entrepreneur(s)",
  "Return on investment vs. risk",
  "Market research",
  "Valuations of ventures",
  "Geographical business location",
  "Market of the early-stage enterprise (geographical)"
)

for(i in 1:(ncol(dataLikert)-1)) {
  colnames(dataLikert)[i] <- cols[[i]]
}

# Show structure of the data
str(dataLikert)

'data.frame':        25 obs. of  11 variables:
 $ Recommendations (e.g. by investors)                 : Ord.factor w/ 5 levels "Unimportant"<..: 4 4 5 3 2 3 4 5 3 3 ...
 $ Historic investment decisions                       : Ord.factor w/ 5 levels "Unimportant"<..: 4 5 2 2 3 2 NA 3 3 3 ...
 $ Relationship to entrepreneur(s)                     : Ord.factor w/ 5 levels "Unimportant"<..: 2 2 2 2 1 4 NA 2 2 4 ...
```

```
 $ Industry sector                                   : Ord.factor w/ 5
 ↪  levels "Unimportant"<..: 5 4 3 5 5 3 5 4 4 4 ...
 $ Experience of entrepreneur(s)                       : Ord.factor w/
 ↪  5 levels "Unimportant"<..: 4 5 4 4 3 4 4 3 5 5 ...
 $ Return on investment vs. risk                       : Ord.factor w/
 ↪  5 levels "Unimportant"<..: 4 5 4 4 5 5 5 4 5 3 ...
 $ Market research                                   : Ord.factor w/ 5
 ↪  levels "Unimportant"<..: 5 5 2 3 5 4 4 2 5 4 ...
 $ Valuations of ventures                              : Ord.factor w/
 ↪  5 levels "Unimportant"<..: 3 4 2 5 5 4 4 4 5 2 ...
 $ Geographical business location                      : Ord.factor w/
 ↪  5 levels "Unimportant"<..: 4 2 1 2 4 2 4 2 3 2 ...
 $ Market of the early-stage enterprise (geographical): Ord.factor w/
 ↪  5 levels "Unimportant"<..: 4 4 3 5 3 4 5 2 4 3 ...
 $ Q3                                                  : Factor w/ 2
 ↪  levels "No","Yes": 2 2 2 2 2 2 NA NA 2 1 ...

# Load fonts for postscript usage
extrafont::loadfonts(device="postscript")

# Plot likert (no histogram) to eps file
postscript(
  file = "./output/q1/q1q3-data-likert-plot-temp.eps",
  paper = "special",
  horizontal = FALSE,
  width = 7.70,
  height = 5.60,
  family = "Linux Libertine Display G",
  fonts = c("Linux Libertine Display G")
)
par(mar=c(0,0,0,0), las=1)
plot(likert::likert(dataLikert[, c(1:(ncol(dataLikert)-1))]),
↪  centered = TRUE, include.histogram = FALSE)
dev.off()

# Embed the designated font(s); device with/height points match eps
↪  with/height times 72
embedFonts(
  file = "./output/q1/q1q3-data-likert-plot-temp.eps",
  outfile = "./output/q1/q1q3-data-likert-plot.eps",
  fontpaths = "/usr/share/fonts/",
  options = "-dDEVICEWIDTHPOINTS=555 -dDEVICEHEIGHTPOINTS=404"
)

# Plot likert (with histogram) to eps file
postscript(
  file = "./output/q1/q1q3-data-likert-histogram-plot-temp.eps",
  paper = "special",
  horizontal = FALSE,
  width = 10.30,
  height = 7.45,
  family = "Linux Libertine Display G",
  fonts = c("Linux Libertine Display G")
```

```
)
par(mar=c(0,0,0,0), las=1)
plot(likert::likert(dataLikert[, c(1:(ncol(dataLikert)-1))]), centered = TRUE, include.histogram = TRUE)
dev.off()

# Embed the designated font(s); device with/height points match eps with/height times 72
embedFonts(
  file = "./output/q1/q1q3-data-likert-histogram-plot-temp.eps",
  outfile = "./output/q1/q1q3-data-likert-histogram-plot.eps",
  fontpaths = "/usr/share/fonts/",
  options = "-dDEVICEWIDTHPOINTS=742 -dDEVICEHEIGHTPOINTS=537"
)

# Plot likert (grouped by Q3; deleted NA answersets)
dataLikertGrouped <- na.omit(dataLikert)
plot(likert::likert(dataLikertGrouped[, c(1:(ncol(dataLikertGrouped)-1))], grouping = dataLikertGrouped$Q3), centered=TRUE, include.histogram = TRUE)
```

Listing 5: Question 1 – Likert Statistics

Wilcoxon Signed Rank Test

```
# Test whether the median of each sub likert question is significantly greater than a hypothized median m = 3
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]], mu=3, conf.int=TRUE, conf.level=0.95, alternative = "greater"))
}

        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 103.5, p-value = 0.005562
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.499937      Inf
sample estimates:
(pseudo)median
      4.000018


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 42.5, p-value = 0.6037
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 2.000008      Inf
```

```
sample estimates:
(pseudo)median
             3


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 78, p-value = 0.6407
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 1.999947      Inf
sample estimates:
(pseudo)median
      2.999989


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 188, p-value = 0.0007481
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
   4 Inf
sample estimates:
(pseudo)median
      4.499992


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 204.5, p-value = 7.033e-05
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 4.000045      Inf
sample estimates:
(pseudo)median
      4.499974


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 204, p-value = 7.494e-05
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 4.000008      Inf
sample estimates:
(pseudo)median
      4.499985
```

```
        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 205, p-value = 0.004123
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.499948      Inf
sample estimates:
(pseudo)median
      3.999977


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 92.5, p-value = 0.03025
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.000072      Inf
sample estimates:
(pseudo)median
      3.999969


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 95, p-value = 0.6591
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 2.5 Inf
sample estimates:
(pseudo)median
      2.999999


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 155, p-value = 0.02746
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.000032      Inf
sample estimates:
(pseudo)median
      3.999935
```

Listing 6: Question 1 – Wilcoxon Signed Rank Test

Wilcoxon Rank Sum Test

```
# Recode Q3 in order for "Yes" being treated as the main response
data$Q3 <- factor(data$Q3, levels = c("Yes", "No"))

# Test whether the location shift for the "No" group to the "Yes"
↪  group is different to 0
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]] ~ Q3, data = data, alternative =
    ↪  "two.sided"))
}

        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 57, p-value = 0.5479
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 46.5, p-value = 0.8724
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 32, p-value = 0.2878
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 58.5, p-value = 0.4797
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 39.5, p-value = 0.4752
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 45, p-value = 0.8267
alternative hypothesis: true location shift is not equal to 0

```

```

        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 38.5, p-value = 0.4339
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 46, p-value = 0.765
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 34.5, p-value = 0.2849
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 50, p-value = 0.9687
alternative hypothesis: true location shift is not equal to 0


# Test whether the location shift for the "No" group to the "Yes"
↪  group is less than 0
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]] ~ Q3, data = data, alternative =
    ↪  "less"))
}

        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 57, p-value = 0.7521
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 46.5, p-value = 0.4362
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
```

```
W = 32, p-value = 0.1439
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 58.5, p-value = 0.7839
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 39.5, p-value = 0.2376
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 45, p-value = 0.6204
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 38.5, p-value = 0.217
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 46, p-value = 0.6497
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 34.5, p-value = 0.1424
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 50, p-value = 0.5468
alternative hypothesis: true location shift is less than 0
```

```
# Test whether the location shift for the "No" group to the "Yes"
↪ group is greater than 0
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]] ~ Q3, data = data, alternative =
    ↪ "greater"))
}

        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 57, p-value = 0.2739
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 46.5, p-value = 0.5952
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 32, p-value = 0.8739
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 58.5, p-value = 0.2399
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 39.5, p-value = 0.7862
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 45, p-value = 0.4134
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 38.5, p-value = 0.8053
```

```
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 46, p-value = 0.3825
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 34.5, p-value = 0.8741
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 50, p-value = 0.4844
alternative hypothesis: true location shift is greater than 0
```

Listing 7: Question 1 – Wilcoxon Rank Sum Test

B.2 Question 2: Which characteristics does an early-stage enterprise need in order for you to consider investing?

Dataset (Likert, ordinal scale 1-5 incl. no specification [NA])

Table B.2: Question 2: dataset (q2q3data.csv); original column names are shortened

Participant	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	Q3
p1	3	3	3	5	2	2	4	2	2	2	4	4	4	Yes
p2	4	4	4	3	2	3	5	1	2	4	4	4	5	Yes
p3	1	1	2	3	2	1	2	3	4	1	4	3	5	Yes
p4	3	3	4	2	2	2	5	5	3	4	4	4	4	Yes
p5	2	2	3	4	2	1	5	3	5	3	5	5	5	Yes
p6	4	5	4	3	4	4	4	4	5	5	4	5	5	Yes
p7	3	3	4	4	4	2	4	3	3	4	5	5	5	NA
p8	2	3	4	4	3	5	4	3	4	5	4	2	5	NA
p9	3	3	4	5	5	5	5	3	2	5	5	5	5	Yes
p10	4	4	4	5	3	3	4	2	2	3	4	2	5	No

To be continued on next page…

…continued from previous page

p11	2	2	1	2	3	2	3	3	3	3	2	1	1	Yes
p12	4	4	4	3	2	2	5	5	5	5	4	3	3	Yes
p13	4	4	5	5	4	3	3	4	5	4	5	4	5	NA
p14	2	2	5	4	3	1	3	3	4	2	4	3	5	Yes
p15	4	4	4	4	3	2	2	4	1	5	4	2	5	Yes
p16	3	3	5	5	2	1	3	5	5	2	5	3	3	No
p17	4	3	3	1	4	5	4	5	4	3	4	3	5	No
p18	2	2	4	2	1	2	5	5	5	2	5	2	5	Yes
p19	3	4	5	5	3	4	4	4	5	4	4	3	4	Yes
p20	3	2	3	3	3	1	1	2	2	3	4	3	4	No
p21	4	4	4	3	3	2	4	4	5	2	4	5	5	NA
p22	4	4	5	5	NA	4	3	4	5	3	2	4	4	No
p23	2	2	2	2	2	3	4	3	2	4	3	3	3	Yes
p24	3	3	5	5	2	3	3	3	3	3	4	4	5	No
p25	5	5	2	2	4	5	2	1	4	5	3	4	1	No

Setup (R dataset)

```
# Read data from CSV
data <- read.csv("q2q3data.csv", row.names=1)

# Show internal structure of the data
str(data, list.len=ncol(data), vec.len=nrow(data))
'data.frame':          25 obs. of  14 variables:
 $ SQ1 : int  3 4 1 3 2 4 3 2 3 4 2 4 4 2 4 3 4 2 3 3 4 4 2 3 5
 $ SQ2 : int  3 4 1 3 2 5 3 3 3 4 2 4 4 2 4 3 3 2 4 2 4 4 2 3 5
 $ SQ3 : int  3 4 2 4 3 4 4 4 4 4 1 4 5 5 4 5 3 4 5 3 4 5 2 5 2
 $ SQ4 : int  5 3 3 2 4 3 4 4 5 5 2 3 5 4 4 5 1 2 5 3 3 5 2 5 2
 $ SQ5 : int  2 2 2 2 2 4 4 3 5 3 3 2 4 3 3 2 4 1 3 3 3 NA 2 2 4
 $ SQ6 : int  2 3 1 2 1 4 2 5 5 3 2 2 3 1 2 1 5 2 4 1 2 4 3 3 5
 $ SQ7 : int  4 5 2 5 5 4 4 4 5 4 3 5 3 3 2 3 4 5 4 1 4 3 4 3 2
 $ SQ8 : int  2 1 3 5 3 4 3 3 3 2 3 5 4 3 4 5 5 5 4 2 4 4 3 3 1
 $ SQ9 : int  2 2 4 3 5 5 3 4 2 2 3 5 5 4 1 5 4 5 5 2 5 5 2 3 4
 $ SQ10: int  2 4 1 4 3 5 4 5 5 3 3 5 4 2 5 2 3 2 4 3 2 3 4 3 5
 $ SQ11: int  4 4 4 4 5 4 5 4 5 4 2 4 5 4 4 5 4 5 4 4 4 2 3 4 3
 $ SQ12: int  4 4 3 4 5 5 5 2 5 2 1 3 4 3 2 3 3 2 3 3 5 4 3 4 4
 $ SQ13: int  4 5 5 4 5 5 5 5 5 5 1 3 5 5 5 3 5 5 4 4 5 4 3 5 1
 $ Q3  : Factor w/ 2 levels "No","Yes": 2 2 2 2 2 2 NA NA 2 1 2 2 NA
 ↪  2 2 1 1 2 2 1 NA 1 2 1 1
```

Listing 8: Question 2 – Setup (R dataset)

Descriptive Statistics

```r
# Print LaTeX table with descriptive statistics
stargazer::stargazer(data, summary.stat = c("n", "mean", "sd", "min", "p25", "median", "p75", "max"))

# Print more detailed descriptive statistics (grouped by Q3; LaTeX table format)
data$Q3 <- factor(data$Q3, levels = c("Yes", "No"))

cat(paste("SQ", " & ",
          "Group", " & ",
          "N", " & ",
          "N (valid)", " & ",
          "Mean", " & ",
          "Std. Dev.", " & ",
          "Min", " & ",
          "Pctl(25)", " & ",
          "Median", " & ",
          "Pctl(75)", " & ",
          "Max",
          sep = ""
    ), sep = "\n"
)
cat("------------------------------------------------------------------------------------", sep = "\n")

for (i in 1:(ncol(data)-1)) {
  statistics <- FSA::Summarize(data[[i]], digits=3, na.rm = TRUE, nvalid = "always", percZero = "always")
  statisticsGrouped <- FSA::Summarize(data[[i]] ~ data$Q3, digits=3, na.rm = TRUE, nvalid = "always", percZero = "always")

  sqindex <- paste("SQ", i, sep = "")

  cat(paste(sqindex, " & ",
            "Overall", " & ",
            statistics[[1]], " & ",
            statistics[[2]], " & ",
            statistics[[3]], " & ",
            statistics[[4]], " & ",
            statistics[[5]], " & ",
            statistics[[6]], " & ",
            statistics[[7]], " & ",
            statistics[[8]], " & ",
            statistics[[9]], "\\\\",
            sep=""),
      sep = "\n"
  )

  ws <- ""

```

```
  for (z in 1:nchar(sqindex)) {
    ws <- paste(ws, " ", sep = "")
  }

  for (j in 1:length(statisticsGrouped$data$Q3)) {
    cat(paste(ws, " & ",
              statisticsGrouped$data$Q3[[j]], " & ",
              statisticsGrouped$n[[j]], " & ",
              statisticsGrouped$nvalid[[j]], " & ",
              statisticsGrouped$mean[[j]], " & ",
              statisticsGrouped$sd[[j]], " & ",
              statisticsGrouped$min[[j]], " & ",
              statisticsGrouped$Q1[[j]], " & ",
              statisticsGrouped$median[[j]], " & ",
              statisticsGrouped$Q3[[j]], " & ",
              statisticsGrouped$max[[j]], "\\\\",
              sep=""),
        sep = "\n"
    )
  }

  cat(paste(ws, "\\hline"), sep = "\n")
}
```

Listing 9: Question 2 – Descriptive Statistics

Test for Normality

```
# Test each sub likert item of the question for normality
for(i in 1:(ncol(data)-1)) {
    print(shapiro.test(data[[i]]))
}

        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.89718, p-value = 0.01593


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.91524, p-value = 0.03997


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.86612, p-value = 0.003621


```

```
        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.87831, p-value = 0.006378


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.89628, p-value = 0.01797


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.88423, p-value = 0.008457


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.89425, p-value = 0.01378


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.90859, p-value = 0.02835


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.8515, p-value = 0.001881


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.90365, p-value = 0.02205


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.78047, p-value = 0.0001093


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.91306, p-value = 0.03569
```

```

        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.67947, p-value = 3.906e-06
```

Listing 10: Question 2 – Test for Normality

Test for Reliability (Cronbach Alpha)

```
# Run the alpha test only for columns data likert columns (i.e.
↪  without column Q3)
psych::alpha(data[, c(1:(ncol(data) - 1))])

Reliability analysis
Call: psych::alpha(x = data[, c(1:(ncol(data) - 1))])

  raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd
      0.72      0.73    0.89      0.17 2.7 0.084  3.5 0.55

 lower alpha upper     95% confidence boundaries
0.55 0.72 0.88

 Reliability if an item is dropped:
     raw_alpha std.alpha G6(smc) average_r S/N alpha se
SQ1       0.69      0.71    0.85      0.17 2.4    0.093
SQ2       0.67      0.69    0.84      0.15 2.2    0.099
SQ3       0.67      0.68    0.85      0.15 2.2    0.100
SQ4       0.72      0.73    0.88      0.18 2.7    0.086
SQ5       0.70      0.72    0.87      0.17 2.5    0.090
SQ6       0.70      0.71    0.87      0.17 2.5    0.090
SQ7       0.71      0.73    0.88      0.18 2.6    0.088
SQ8       0.73      0.74    0.89      0.19 2.8    0.083
SQ9       0.72      0.73    0.88      0.19 2.8    0.083
SQ10      0.70      0.72    0.87      0.17 2.5    0.089
SQ11      0.71      0.72    0.88      0.18 2.6    0.088
SQ12      0.69      0.71    0.88      0.17 2.4    0.093
SQ13      0.71      0.72    0.88      0.18 2.6    0.087

 Item statistics
      n raw.r std.r r.cor r.drop mean   sd
SQ1  25  0.55  0.56  0.58   0.44  3.1 0.97
SQ2  25  0.68  0.69  0.71   0.59  3.2 1.03
SQ3  25  0.71  0.70  0.71   0.61  3.7 1.10
SQ4  25  0.41  0.40  0.37   0.24  3.6 1.26
SQ5  24  0.47  0.48  0.45   0.35  2.8 0.96
SQ6  25  0.52  0.50  0.47   0.35  2.7 1.37
SQ7  25  0.42  0.41  0.36   0.28  3.6 1.11
SQ8  25  0.33  0.31  0.25   0.16  3.4 1.19
SQ9  25  0.38  0.34  0.30   0.19  3.6 1.32
SQ10 25  0.47  0.48  0.46   0.34  3.4 1.19
```

```
SQ11 25   0.40  0.44  0.40   0.31  4.0 0.82
SQ12 25   0.55  0.56  0.50   0.42  3.4 1.12
SQ13 25   0.43  0.45  0.41   0.29  4.2 1.20

Non missing response frequency for each item
        1    2    3    4    5 miss
SQ1  0.04 0.24 0.32 0.36 0.04 0.00
SQ2  0.04 0.24 0.32 0.32 0.08 0.00
SQ3  0.04 0.12 0.16 0.44 0.24 0.00
SQ4  0.04 0.20 0.24 0.20 0.32 0.00
SQ5  0.04 0.38 0.33 0.21 0.04 0.04
SQ6  0.20 0.32 0.20 0.12 0.16 0.00
SQ7  0.04 0.12 0.24 0.36 0.24 0.00
SQ8  0.08 0.12 0.36 0.24 0.20 0.00
SQ9  0.04 0.24 0.16 0.20 0.36 0.00
SQ10 0.04 0.20 0.28 0.24 0.24 0.00
SQ11 0.00 0.08 0.08 0.60 0.24 0.00
SQ12 0.04 0.16 0.32 0.28 0.20 0.00
SQ13 0.08 0.00 0.12 0.20 0.60 0.00
```

Listing 11: Question 2 – Test for Reliability (Cronbach Alpha)

Likert Statistics

```
# Load grid library needed for likert processing (at least in case of
↪ a Linux system)
library(grid)

# Define levels
levels = c("Unimportant", "Rather unimportant", "Neutral", "Rather
↪ important", "Essential")

# Copy data
dataLikert <- data

# Rename responds
for(i in 1:(ncol(dataLikert)-1)) {
  dataLikert[[i]] = likert::recode(dataLikert[[i]], from=c(1, 2, 3,
  ↪ 4, 5), to=levels)
}

# Replace columns with an ordered factor
for(i in 1:(ncol(dataLikert)-1)) {
  dataLikert[[i]] = factor(dataLikert[[i]], levels = levels,
  ↪ ordered = TRUE)
}

# Rename columns
cols = c(
  "Team: Former experience as CEO",
  "Team: Former experience as COO, CFO, CTO",
```

```
  "Team: Existent knowledge to implement the product idea",
  "Team: Founder team consists of min. 2 persons",
  "Team: Founder is willing to step back (if needed)",
  "Team: Own funds at time of foundation",
  "Product idea elaborated (prototype implemented)",
  "Product idea elaborated (prototype not implemented)",
  "Product idea available and rudimentarily elaborated",
  "Product idea protected by patents",
  "Industry sector is not saturated. Market entry of the product idea
   ↪  possible",
  "Market analysis / Industry sector analysis / venture valuation
   ↪  available",
  "Plausibility of the enterprise formation"
)

for(i in 1:(ncol(dataLikert)-1)) {
  colnames(dataLikert)[i] <- cols[[i]]
}

# Show structure of the data
str(dataLikert)

'data.frame':        25 obs. of  14 variables:
 $ Team: Former experience as CEO
  ↪  : Ord.factor w/ 5 levels "Unimportant"<..: 3 4 1 3 2 4 3 2 3 4
  ↪  ...
 $ Team: Former experience as COO, CFO, CTO
  ↪  : Ord.factor w/ 5 levels "Unimportant"<..: 3 4 1 3 2 5 3 3 3 4
  ↪  ...
 $ Team: Existent knowledge to implement the product idea
  ↪  : Ord.factor w/ 5 levels "Unimportant"<..: 3 4 2 4 3 4 4 4 4 4
  ↪  ...
 $ Team: Founder team consists of min. 2 persons
  ↪  : Ord.factor w/ 5 levels "Unimportant"<..: 5 3 3 2 4 3 4 4 5 5
  ↪  ...
 $ Team: Founder is willing to step back (if needed)
  ↪  : Ord.factor w/ 5 levels "Unimportant"<..: 2 2 2 2 2 4 4 3 5 3
  ↪  ...
 $ Team: Own funds at time of foundation
  ↪  : Ord.factor w/ 5 levels "Unimportant"<..: 2 3 1 2 1 4 2 5 5 3
  ↪  ...
 $ Product idea elaborated (prototype implemented)
  ↪  : Ord.factor w/ 5 levels "Unimportant"<..: 4 5 2 5 5 4 4 4 5 4
  ↪  ...
 $ Product idea elaborated (prototype not implemented)
  ↪  : Ord.factor w/ 5 levels "Unimportant"<..: 2 1 3 5 3 4 3 3 3 2
  ↪  ...
 $ Product idea available and rudimentarily elaborated
  ↪  : Ord.factor w/ 5 levels "Unimportant"<..: 2 2 4 3 5 5 3 4 2 2
  ↪  ...
 $ Product idea protected by patents
  ↪  : Ord.factor w/ 5 levels "Unimportant"<..: 2 4 1 4 3 5 4 5 5 3
  ↪  ...
```

```
 $ Industry sector is not saturated. Market entry of the product idea possible: Ord.factor w/ 5 levels "Unimportant"<..: 4 4 4 4 5 4 5 4 5 4 ...
 $ Market analysis / Industry sector analysis / venture valuation available   : Ord.factor w/ 5 levels "Unimportant"<..: 4 4 3 4 5 5 5 2 5 2 ...
 $ Plausibility of the enterprise formation : Ord.factor w/ 5 levels "Unimportant"<..: 4 5 5 4 5 5 5 5 5 5 ...
 $ Q3 : Factor w/ 2 levels "No","Yes": 2 2 2 2 2 2 NA NA 2 1 ...

# Load fonts for postscript usage
extrafont::loadfonts(device="postscript")

# Plot likert (no histogram) to eps file
postscript(
  file = "./output/q2/q2q3-data-likert-plot-temp.eps",
  paper = "special",
  horizontal = FALSE,
  width = 8.45,
  height = 6.15,
  family = "Linux Libertine Display G",
  fonts = c("Linux Libertine Display G")
)
par(mar=c(0,0,0,0), las=1)
plot(likert::likert(dataLikert[, c(1:(ncol(dataLikert)-1))]), centered = TRUE, include.histogram = FALSE)
dev.off()

# Embed the designated font(s); device with/height points match eps with/height times 72
embedFonts(
  file = "./output/q2/q2q3-data-likert-plot-temp.eps",
  outfile = "./output/q2/q2q3-data-likert-plot.eps",
  fontpaths = "/usr/share/fonts/",
  options = "-dDEVICEWIDTHPOINTS=609 -dDEVICEHEIGHTPOINTS=443"
)

# Plot likert (with histogram) to eps file
postscript(
  file = "./output/q2/q2q3-data-likert-histogram-plot-temp.eps",
  paper = "special",
  horizontal = FALSE,
  width = 11.20,
  height = 8.15,
  family = "Linux Libertine Display G",
  fonts = c("Linux Libertine Display G")
)
par(mar=c(0,0,0,0), las=1)
plot(likert::likert(dataLikert[, c(1:(ncol(dataLikert)-1))]), centered = TRUE, include.histogram = TRUE)
dev.off()
```

```
# Embed the designated font(s); device with/height points match eps
↪ with/height times 72
embedFonts(
  file = "./output/q2/q2q3-data-likert-histogram-plot-temp.eps",
  outfile = "./output/q2/q2q3-data-likert-histogram-plot.eps",
  fontpaths = "/usr/share/fonts/",
  options = "-dDEVICEWIDTHPOINTS=807 -dDEVICEHEIGHTPOINTS=587"
)

# Plot likert (with histogram) to svg file
svg(
  file = "./output/q2/q2q3-data-likert-histogram-plot.svg",
  width = 11.20,
  height = 8.15,
  family = "Linux Libertine Display G"
)
par(mar=c(0,0,0,0), las=1)
plot(likert::likert(dataLikert[, c(1:(ncol(dataLikert)-1))]),
↪ centered = TRUE, include.histogram = TRUE)
dev.off()

# Plot likert (grouped by Q3; deleted NA answersets)
dataLikertGrouped <- na.omit(dataLikert)
plot(likert::likert(dataLikertGrouped[,
↪ c(1:(ncol(dataLikertGrouped)-1))], grouping =
↪ dataLikertGrouped$Q3), centered=TRUE, include.histogram = TRUE)
```

Listing 12: Question 2 – Likert Statistics

Wilcoxon Signed Rank Test

```
# Test whether the median of each sub likert question is
↪ significantly greater than a hypothized median m = 3
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]], mu=3, conf.int=TRUE,
    ↪ conf.level=0.95, alternative = "greater"))
}

        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 88.5, p-value = 0.2766
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 2.999975      Inf
sample estimates:
(pseudo)median
             3


```

```
        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 92, p-value = 0.2234
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 2.999986      Inf
sample estimates:
(pseudo)median
      3.000024


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 190.5, p-value = 0.003514
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.499976      Inf
sample estimates:
(pseudo)median
      4.000049


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 147.5, p-value = 0.01555
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.000057      Inf
sample estimates:
(pseudo)median
      3.500039


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 53, p-value = 0.808
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 2.00002      Inf
sample estimates:
(pseudo)median
      2.999932


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 82, p-value = 0.8171
alternative hypothesis: true location is greater than 3
```

```
95 percent confidence interval:
 1.999942       Inf
sample estimates:
(pseudo)median
      2.500031


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 154.5, p-value = 0.006927
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.499973       Inf
sample estimates:
(pseudo)median
      4.000003


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 95, p-value = 0.07891
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 2.999957       Inf
sample estimates:
(pseudo)median
      3.500009


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 178.5, p-value = 0.0126
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.000006       Inf
sample estimates:
(pseudo)median
      3.500056


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 126, p-value = 0.03578
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.00007      Inf
sample estimates:
(pseudo)median
      3.500054
```

```


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 258, p-value = 6.465e-05
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.99995      Inf
sample estimates:
(pseudo)median
      4.000008


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 114.5, p-value = 0.03272
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.000043      Inf
sample estimates:
(pseudo)median
      3.999923


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 225, p-value = 0.000372
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 4.499957      Inf
sample estimates:
(pseudo)median
      4.500033
```

Listing 13: Question 2 – Wilcoxon Signed Rank Test

Wilcoxon Rank Sum Test

```
# Recode Q3 in order for "Yes" being treated as the main response
data$Q3 <- factor(data$Q3, levels = c("Yes", "No"))

# Test whether the location shift for the "No" group to the "Yes"
↪ group is different to 0
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]] ~ Q3, data = data, alternative =
    ↪ "two.sided"))
}

```

```
        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 24, p-value = 0.05593
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 36.5, p-value = 0.3535
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 40.5, p-value = 0.5345
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 40, p-value = 0.512
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 30, p-value = 0.3121
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 36, p-value = 0.3393
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 76, p-value = 0.04132
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 55, p-value = 0.6723
```

```
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 47, p-value = 0.9077
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 58.5, p-value = 0.4881
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 57.5, p-value = 0.4924
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 51, p-value = 0.907
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 56.5, p-value = 0.569
alternative hypothesis: true location shift is not equal to 0


# Test whether the location shift for the "No" group to the "Yes"
↪ group is less than 0
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]] ~ Q3, data = data, alternative =
    ↪ "less"))
}

        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 24, p-value = 0.02797
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction
```

```

data:  data[[i]] by Q3
W = 36.5, p-value = 0.1768
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 40.5, p-value = 0.2673
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 40, p-value = 0.256
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 30, p-value = 0.156
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 36, p-value = 0.1697
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 76, p-value = 0.9829
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 55, p-value = 0.6914
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 47, p-value = 0.4539
alternative hypothesis: true location shift is less than 0
```

```


	Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 58.5, p-value = 0.7795
alternative hypothesis: true location shift is less than 0


	Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 57.5, p-value = 0.78
alternative hypothesis: true location shift is less than 0


	Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 51, p-value = 0.5772
alternative hypothesis: true location shift is less than 0


	Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 56.5, p-value = 0.7424
alternative hypothesis: true location shift is less than 0


# Test whether the location shift for the "No" group to the "Yes"
↪  group is greater than 0
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]] ~ Q3, data = data, alternative =
    ↪  "greater"))
}

	Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 24, p-value = 0.9767
alternative hypothesis: true location shift is greater than 0


	Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 36.5, p-value = 0.8426
alternative hypothesis: true location shift is greater than 0


	Wilcoxon rank sum test with continuity correction

```

```
data:  data[[i]] by Q3
W = 40.5, p-value = 0.7576
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 40, p-value = 0.7682
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 30, p-value = 0.8641
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 36, p-value = 0.8489
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 76, p-value = 0.02066
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 55, p-value = 0.3361
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 47, p-value = 0.5766
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 58.5, p-value = 0.244
alternative hypothesis: true location shift is greater than 0

```

```

        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 57.5, p-value = 0.2462
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 51, p-value = 0.4535
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 56.5, p-value = 0.2845
alternative hypothesis: true location shift is greater than 0
```

Listing 14: Question 2 – Wilcoxon Rank Sum Test

B.3 Question 3: Are you able to predict the success/failure of an early-stage enterprise in the (pre-)seed stage?

Dataset (dichotomous/binary, Yes/No incl. no specification [NA])

Table B.3: Question 3: dataset (q3data.csv)

Participant	Q3
p1	Yes
p2	Yes
p3	Yes
p4	Yes
p5	Yes
p6	Yes
p7	NA
p8	NA
p9	Yes
p10	No
p11	Yes

To be continued on next page…

…continued from previous page

p12	Yes
p13	NA
p14	Yes
p15	Yes
p16	No
p17	No
p18	Yes
p19	Yes
p20	No
p21	NA
p22	No
p23	Yes
p24	No
p25	No

Setup (R dataset)

```
# Read data from CSV
data <- read.csv("q3data.csv", row.names=1)

# Show internal structure of the data
str(data, list.len=ncol(data), vec.len=nrow(data))
'data.frame':        25 obs. of  1 variable:
 $ Q3: Factor w/ 2 levels "No","Yes": 2 2 2 2 2 2 NA NA 2 1 2 2 NA 2 2 1 1 2 2 1 NA 1 2 1 1
```

Listing 15: Question 3 – Setup (R dataset)

Descriptive Statistics

```
# Print descriptive statistics
summary(data)
    Q3
 No  : 7
 Yes :14
 NA's: 4
```

Listing 16: Question 3 – Descriptive Statistics

B.4 Question 4: Which characteristics of early-stage enterprises are important for venture valuations?

Dataset (Likert, ordinal scale 1-5 incl. no specification [NA])

Table B.4: Question 4: dataset (q4q3data.csv)

Participant	SQ1	SQ2	SQ3	SQ4	SQ5	SQ6	SQ7	SQ8	SQ9	Q3
p1	4	4	4	2	4	4	NA	4	5	Yes
p2	5	3	4	3	4	4	3	4	4	Yes
p3	4	2	3	1	5	3	3	4	2	Yes
p4	3	4	4	3	4	4	2	3	3	Yes
p5	5	4	4	1	5	5	4	3	3	Yes
p6	5	4	5	3	4	4	2	5	4	Yes
p7	5	4	4	2	5	4	3	4	2	NA
p8	5	4	3	3	5	4	4	4	4	NA
p9	5	5	5	3	5	5	5	3	2	Yes
p10	2	5	4	2	4	4	5	3	3	No
p11	2	2	2	2	2	2	2	3	3	Yes
p12	3	5	5	3	4	3	5	5	4	Yes
p13	5	4	5	3	4	4	5	5	4	NA
p14	4	4	4	2	3	2	1	2	2	Yes
p15	5	3	5	2	4	5	4	4	5	Yes
p16	5	5	5	2	4	4	2	3	3	No
p17	5	4	4	5	3	4	2	4	1	No
p18	2	5	4	2	5	5	2	5	5	Yes
p19	5	3	5	2	4	3	5	5	4	Yes
p20	5	1	3	1	4	3	2	3	2	No
p21	5	5	5	1	4	4	2	4	3	NA
p22	5	4	5	2	5	4	NA	NA	NA	No
p23	3	2	5	3	3	4	3	4	2	Yes
p24	3	3	4	3	4	4	2	4	3	No
p25	2	2	1	5	3	4	2	4	5	No

Setup (R dataset)

```r
# Read data from CSV
data <- read.csv("q4q3data.csv", row.names=1)

```

```
# Show internal structure of the data
str(data, list.len=ncol(data), vec.len=nrow(data))
'data.frame':        25 obs. of  10 variables:
 $ SQ1: int  4 5 4 3 5 5 5 5 5 2 2 3 5 4 5 5 5 2 5 5 5 5 3 3 2
 $ SQ2: int  4 3 2 4 4 4 4 4 5 5 2 5 4 4 3 5 4 5 3 1 5 4 2 3 2
 $ SQ3: int  4 4 3 4 4 5 4 3 5 4 2 5 5 4 5 5 4 4 5 3 5 5 5 4 1
 $ SQ4: int  2 3 1 3 1 3 2 3 3 2 2 3 3 2 2 2 5 2 2 1 1 2 3 3 5
 $ SQ5: int  4 4 5 4 5 4 5 5 5 4 2 4 4 3 4 4 3 5 4 4 4 5 3 4 3
 $ SQ6: int  4 4 3 4 5 4 4 4 5 4 2 3 4 2 5 4 4 5 3 3 4 4 4 4 4
 $ SQ7: int  NA 3 3 2 4 2 3 4 5 5 2 5 5 1 4 2 2 2 5 2 2 NA 3 2 2
 $ SQ8: int  4 4 4 3 3 5 4 4 3 3 3 5 5 2 4 3 4 5 5 3 4 NA 4 4 4
 $ SQ9: int  5 4 2 3 3 4 2 4 2 3 3 4 4 2 5 3 1 5 4 2 3 NA 2 3 5
 $ Q3 : Factor w/ 2 levels "No","Yes": 2 2 2 2 2 2 NA NA 2 1 2 2 NA 2
 ↪  2 1 1 2 2 1 NA 1 2 1 1
```

Listing 17: Question 4 – Setup (R dataset)

Descriptive Statistics

```
# Print LaTeX table with descriptive statistics
stargazer::stargazer(data, summary.stat = c("n", "mean", "sd", "min",
↪  "p25", "median", "p75", "max"))

# Print more detailed descriptive statistics (grouped by Q3; LaTeX
↪  table format)
data$Q3 <- factor(data$Q3, levels = c("Yes", "No"))

cat(paste("SQ", " & ",
          "Group", " & ",
          "N", " & ",
          "N (valid)", " & ",
          "Mean", " & ",
          "Std. Dev.", " & ",
          "Min", " & ",
          "Pctl(25)", " & ",
          "Median", " & ",
          "Pctl(75)", " & ",
          "Max",
          sep = ""
    ), sep = "\n"
)
cat("---------------------------------------------------------------
↪  -------------------------", sep =
↪  "\n")

for (i in 1:(ncol(data)-1)) {
  statistics <- FSA::Summarize(data[[i]], digits=3, na.rm = TRUE,
   ↪  nvalid = "always", percZero = "always")
  statisticsGrouped <- FSA::Summarize(data[[i]] ~ data$Q3, digits=3,
   ↪  na.rm = TRUE, nvalid = "always", percZero = "always")

```

```
    sqindex <- paste("SQ", i, sep = "")

    cat(paste(sqindex, " & ",
              "Overall", " & ",
              statistics[[1]], " & ",
              statistics[[2]], " & ",
              statistics[[3]], " & ",
              statistics[[4]], " & ",
              statistics[[5]], " & ",
              statistics[[6]], " & ",
              statistics[[7]], " & ",
              statistics[[8]], " & ",
              statistics[[9]], "\\\\",
              sep=""),
        sep = "\n"
    )

    ws <- ""

    for (z in 1:nchar(sqindex)) {
      ws <- paste(ws, " ", sep = "")
    }

    for (j in 1:length(statisticsGrouped$data$Q3)) {
      cat(paste(ws, " & ",
                statisticsGrouped$data$Q3[[j]], " & ",
                statisticsGrouped$n[[j]], " & ",
                statisticsGrouped$nvalid[[j]], " & ",
                statisticsGrouped$mean[[j]], " & ",
                statisticsGrouped$sd[[j]], " & ",
                statisticsGrouped$min[[j]], " & ",
                statisticsGrouped$Q1[[j]], " & ",
                statisticsGrouped$median[[j]], " & ",
                statisticsGrouped$Q3[[j]], " & ",
                statisticsGrouped$max[[j]], "\\\\",
                sep=""),
          sep = "\n"
      )
    }

    cat(paste(ws, "\\hline"), sep = "\n")
}
```

Listing 18: Question 4 – Descriptive Statistics

Test for Normality

```
# Test each sub likert item of the question for normality
for(i in 1:(ncol(data)-1)) {
    print(shapiro.test(data[[i]]))
}
```

```

        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.73603, p-value = 2.316e-05


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.87786, p-value = 0.006244


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.79592, p-value = 0.0001945


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.84576, p-value = 0.001465


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.83484, p-value = 0.0009202


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.81299, p-value = 0.0003775


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.83702, p-value = 0.001597


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.86591, p-value = 0.004378


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.91389, p-value = 0.04287
```

Listing 19: Question 4 – Test for Normality

Test for Reliability (Cronbach Alpha)

```
# Run the alpha test only for columns data likert columns (i.e. without column Q3)
psych::alpha(data[, c(1:(ncol(data) - 1))])

Some items ( SQ4 ) were negatively correlated with the total scale and
probably should be reversed.
To do this, run the function again with the 'check.keys=TRUE' option
Reliability analysis
Call: psych::alpha(x = data[, c(1:(ncol(data) - 1))])

  raw_alpha std.alpha G6(smc) average_r S/N ase mean   sd
      0.65      0.68    0.82      0.19 2.1 0.1  3.6 0.54

 lower alpha upper     95% confidence boundaries
0.45 0.65 0.86

 Reliability if an item is dropped:
    raw_alpha std.alpha G6(smc) average_r S/N alpha se
SQ1      0.66      0.68    0.81      0.21 2.1    0.102
SQ2      0.60      0.63    0.76      0.18 1.7    0.120
SQ3      0.59      0.62    0.72      0.17 1.7    0.124
SQ4      0.71      0.73    0.79      0.26 2.8    0.088
SQ5      0.61      0.63    0.72      0.18 1.7    0.119
SQ6      0.59      0.61    0.75      0.16 1.5    0.122
SQ7      0.59      0.63    0.80      0.18 1.7    0.124
SQ8      0.61      0.63    0.75      0.18 1.7    0.116
SQ9      0.66      0.68    0.79      0.21 2.1    0.101

 Item statistics
     n raw.r std.r r.cor r.drop mean   sd
SQ1 25  0.45  0.42  0.33   0.21  4.1 1.19
SQ2 25  0.61  0.60  0.56   0.43  3.6 1.15
SQ3 25  0.66  0.64  0.63   0.50  4.1 1.04
SQ4 25  0.12  0.14  0.05  -0.08  2.4 1.04
SQ5 25  0.60  0.62  0.62   0.46  4.0 0.79
SQ6 25  0.66  0.70  0.68   0.56  3.8 0.80
SQ7 23  0.64  0.62  0.52   0.45  3.0 1.30
SQ8 24  0.58  0.60  0.57   0.45  3.8 0.82
SQ9 24  0.43  0.43  0.35   0.20  3.2 1.15

Non missing response frequency for each item
       1    2    3    4    5 miss
SQ1 0.00 0.16 0.16 0.12 0.56 0.00
SQ2 0.04 0.16 0.16 0.40 0.24 0.00
SQ3 0.04 0.04 0.12 0.40 0.40 0.00
SQ4 0.16 0.40 0.36 0.00 0.08 0.00
SQ5 0.00 0.04 0.16 0.52 0.28 0.00
```

```
SQ6 0.00 0.08 0.16 0.60 0.16 0.00
SQ7 0.04 0.43 0.17 0.13 0.22 0.08
SQ8 0.00 0.04 0.29 0.46 0.21 0.04
SQ9 0.04 0.25 0.29 0.25 0.17 0.04
Warning message:
In psych::alpha(data[, c(1:(ncol(data) - 1))]) :
  Some items were negatively correlated with the total scale and probably
should be reversed.
To do this, run the function again with the 'check.keys=TRUE' option
```

Listing 20: Question 4 – Test for Reliability (Cronbach Alpha)

Likert Statistics

```
# Load grid library needed for likert processing (at least in case of a Linux system)
library(grid)

# Define levels
levels = c("Unimportant", "Rather unimportant", "Neutral", "Rather important", "Important")

# Copy data
dataLikert <- data

# Rename responds
for(i in 1:(ncol(dataLikert)-1)) {
  dataLikert[[i]] = likert::recode(dataLikert[[i]], from=c(1, 2, 3, 4, 5), to=levels)
}

# Replace columns with an ordered factor
for(i in 1:(ncol(dataLikert)-1)) {
  dataLikert[[i]] = factor(dataLikert[[i]], levels = levels, ordered = TRUE)
}

# Rename columns
cols = c(
  "Opportunity (market situation, revenue in 5 years)",
  "Maturity level of the product idea",
  "Customer acceptance of the product idea",
  "Equity capital / financial assets of the founders",
  "Industry structure (market entry barriers, market growth)",
  "Competition",
  "Number of founders > 1",
  "Experience of the founder team",
  "Founders already have experience in founding- and running early-stage enterprises"
)
```

```
for(i in 1:(ncol(dataLikert)-1)) {
  colnames(dataLikert)[i] <- cols[[i]]
}

# Show structure of the data
str(dataLikert)

'data.frame':        25 obs. of  10 variables:
 $ Opportunity (market situation, revenue in 5 years)
 ↪   : Ord.factor w/ 5 levels "Unimportant"<..: 4 5 4 3 5 5 5 5 5 2
 ↪   ...
 $ Maturity level of the product idea
 ↪   : Ord.factor w/ 5 levels "Unimportant"<..: 4 3 2 4 4 4 4 4 5 5
 ↪   ...
 $ Customer acceptance of the product idea
 ↪   : Ord.factor w/ 5 levels "Unimportant"<..: 4 4 3 4 4 5 4 3 5 4
 ↪   ...
 $ Equity capital / financial assets of the founders
 ↪   : Ord.factor w/ 5 levels "Unimportant"<..: 2 3 1 3 1 3 2 3 3 2
 ↪   ...
 $ Industry structure (market entry barriers, market growth)
 ↪   : Ord.factor w/ 5 levels "Unimportant"<..: 4 4 5 4 5 4 5 5 5 4
 ↪   ...
 $ Competition
 ↪   : Ord.factor w/ 5 levels "Unimportant"<..: 4 4 3 4 5 4 4 4 5 4
 ↪   ...
 $ Number of founders > 1
 ↪   : Ord.factor w/ 5 levels "Unimportant"<..: NA 3 3 2 4 2 3 4 5 5
 ↪   ...
 $ Experience of the founder team
 ↪   : Ord.factor w/ 5 levels "Unimportant"<..: 4 4 4 3 3 5 4 4 3 3
 ↪   ...
 $ Founders already have experience in founding- and running
 ↪   early-stage enterprises: Ord.factor w/ 5 levels
 ↪   "Unimportant"<..: 5 4 2 3 3 4 2 4 2 3 ...
 $ Q3
 ↪   : Factor w/ 2 levels "No","Yes": 2 2 2 2 2 2 NA NA 2 1 ...

# Load fonts for postscript usage
extrafont::loadfonts(device="postscript")

# Plot likert (no histogram) to eps file
postscript(
  file = "./output/q4/q4q3-data-likert-plot-temp.eps",
  paper = "special",
  horizontal = FALSE,
  width = 8.45,
  height = 6.15,
  family = "Linux Libertine Display G",
  fonts = c("Linux Libertine Display G")
)
par(mar=c(0,0,0,0), las=1)
```

```
plot(likert::likert(dataLikert[, c(1:(ncol(dataLikert)-1))]),
  ↪ centered = TRUE, include.histogram = FALSE)
dev.off()

# Embed the designated font(s); device with/height points match eps
  ↪ with/height times 72
embedFonts(
  file = "./output/q4/q4q3-data-likert-plot-temp.eps",
  outfile = "./output/q4/q4q3-data-likert-plot.eps",
  fontpaths = "/usr/share/fonts/",
  options = "-dDEVICEWIDTHPOINTS=609 -dDEVICEHEIGHTPOINTS=443"
)

# Plot likert (with histogram) to eps file
postscript(
  file = "./output/q4/q4q3-data-likert-histogram-plot-temp.eps",
  paper = "special",
  horizontal = FALSE,
  width = 11.25,
  height = 8.20,
  family = "Linux Libertine Display G",
  fonts = c("Linux Libertine Display G")
)
par(mar=c(0,0,0,0), las=1)
plot(likert::likert(dataLikert[, c(1:(ncol(dataLikert)-1))]),
  ↪ centered = TRUE, include.histogram = TRUE)
dev.off()

# Embed the designated font(s); device with/height points match eps
  ↪ with/height times 72
embedFonts(
  file = "./output/q4/q4q3-data-likert-histogram-plot-temp.eps",
  outfile = "./output/q4/q4q3-data-likert-histogram-plot.eps",
  fontpaths = "/usr/share/fonts/",
  options = "-dDEVICEWIDTHPOINTS=810 -dDEVICEHEIGHTPOINTS=591"
)

# Plot likert (with histogram) to svg file
svg(
  file = "./output/q4/q4q3-data-likert-histogram-plot.svg",
  width = 11.25,
  height = 8.20,
  family = "Linux Libertine Display G"
)
par(mar=c(0,0,0,0), las=1)
plot(likert::likert(dataLikert[, c(1:(ncol(dataLikert)-1))]),
  ↪ centered = TRUE, include.histogram = TRUE)
dev.off()

# Plot likert (grouped by Q3; deleted NA answersets)
dataLikertGrouped <- na.omit(dataLikert)
```

```
plot(likert::likert(dataLikertGrouped[,
↪  c(1:(ncol(dataLikertGrouped)-1))], grouping =
↪  dataLikertGrouped$Q3), centered=TRUE, include.histogram = TRUE)
```

Listing 21: Question 4 – Likert Statistics

Wilcoxon Signed Rank Test

```
# Test whether the median of each sub likert question is
↪  significantly greater than a hypothized median m = 3
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]], mu=3, conf.int=TRUE,
    ↪  conf.level=0.95, alternative = "greater"))
}

        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 215, p-value = 0.0001705
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.500002      Inf
sample estimates:
(pseudo)median
      4.500015


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 183, p-value = 0.007672
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.000007      Inf
sample estimates:
(pseudo)median
      3.999971


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 230, p-value = 0.0002852
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 4.000064      Inf
sample estimates:
(pseudo)median
      4.499983
```

```
        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 27, p-value = 0.9868
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 1.500033      Inf
sample estimates:
(pseudo)median
      1.999974


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 223.5, p-value = 5.022e-05
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 4.000056      Inf
sample estimates:
(pseudo)median
      4.499967


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 213, p-value = 0.0001568
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.999988      Inf
sample estimates:
(pseudo)median
      4.000005


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 103.5, p-value = 0.3685
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 2.000035      Inf
sample estimates:
(pseudo)median
      3.000024


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 146.5, p-value = 0.00029
alternative hypothesis: true location is greater than 3
```

```
95 percent confidence interval:
 3.999994       Inf
sample estimates:
(pseudo)median
      4.000024


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 99, p-value = 0.138
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 2.999924       Inf
sample estimates:
(pseudo)median
      3.499981
```

Listing 22: Question 4 – Wilcoxon Signed Rank Test

Wilcoxon Rank Sum Test

```
# Recode Q3 in order for "Yes" being treated as the main response
data$Q3 <- factor(data$Q3, levels = c("Yes", "No"))

# Test whether the location shift for the "No" group to the "Yes" group is different to 0
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]] ~ Q3, data = data, alternative = "two.sided"))
}

        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 48.5, p-value = 1
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 50, p-value = 0.9693
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 59.5, p-value = 0.423
alternative hypothesis: true location shift is not equal to 0
```

```


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 43, p-value = 0.6623
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 56, p-value = 0.5962
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 49.5, p-value = 1
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 51.5, p-value = 0.2623
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 52.5, p-value = 0.3812
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 53, p-value = 0.3726
alternative hypothesis: true location shift is not equal to 0


# Test whether the location shift for the "No" group to the "Yes" group is less than 0
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]] ~ Q3, data = data, alternative = "less"))
}

        Wilcoxon rank sum test with continuity correction

```

```
data:  data[[i]] by Q3
W = 48.5, p-value = 0.5
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 50, p-value = 0.546
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 59.5, p-value = 0.811
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 43, p-value = 0.3311
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 56, p-value = 0.7295
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 49.5, p-value = 0.5324
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 51.5, p-value = 0.8877
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 52.5, p-value = 0.8323
alternative hypothesis: true location shift is less than 0
```

```

        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 53, p-value = 0.8356
alternative hypothesis: true location shift is less than 0


# Test whether the location shift for the "No" group to the "Yes" group is greater than 0
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]] ~ Q3, data = data, alternative = "greater"))
}

        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 48.5, p-value = 0.5317
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 50, p-value = 0.4846
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 59.5, p-value = 0.2115
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 43, p-value = 0.6971
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 56, p-value = 0.2981
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
```

```
W = 49.5, p-value = 0.5
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 51.5, p-value = 0.1312
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 52.5, p-value = 0.1906
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 53, p-value = 0.1863
alternative hypothesis: true location shift is greater than 0
```

Listing 23: Question 4 – Wilcoxon Rank Sum Test

B.5 Question 5: Due to the fact that early-stage enterprises of the (pre-) seed stage lack a historic track record of business activities, a valuation is hardly feasible or completely impossible. Therefore, especially business angels utilize self-defined best practices and rules of thumb as valuation methods, which are already discussed by scientific literature. Which of the following valuation methods do you use?

Dataset (categorical, nominal scale, four groups incl. no specification [NA])

Scale (German):

1... Kenne ich nicht (schließt Nutzung aus)

2... Kenne ich (schließt Nutzung aus)

3... Nutze ich nicht (schließt Kenntnis ein)

4... Nutze ich (schließt Kenntnis ein)

NA Keine Angabe

Table B.5: Question 5: dataset (q5q3datanumeric.csv); original column names are shortened

Participant	SQ1	SQ2	SQ3	SQ4	SQ5	SQ6	SQ7	Q3
p1	2	1	1	4	2	2	4	Yes
p2	2	2	3	4	1	1	4	Yes
p3	3	1	1	3	1	1	4	Yes
p4	2	3	2	3	3	3	4	Yes
p5	3	3	2	2	2	3	4	Yes
p6	3	3	4	3	3	3	4	Yes
p7	3	1	3	3	1	2	4	NA
p8	3	1	1	1	1	1	4	NA
p9	4	1	1	1	1	1	4	Yes
p10	4	1	1	4	1	4	3	No
p11	NA	NA	NA	NA	NA	NA	2	Yes
p12	4	3	4	3	3	3	4	Yes
p13	4	1	1	4	1	2	NA	NA
p14	2	1	1	3	1	3	4	Yes
p15	1	1	3	4	1	3	4	Yes
p16	4	3	3	4	3	3	4	No
p17	3	3	3	3	3	3	4	No
p18	2	1	2	4	1	2	4	Yes
p19	NA	NA	NA	NA	NA	NA	NA	Yes
p20	3	1	1	1	1	3	4	No
p21	4	NA	NA	NA	NA	NA	4	NA
p22	2	1	2	2	1	1	4	No
p23	3	1	1	1	3	3	3	Yes
p24	3	1	3	3	1	3	4	No
p25	2	2	2	2	1	1	4	No

Setup (R dataset)

```r
# Read data from CSV
data <- read.csv("q5q3data.csv", encoding="UTF-8", row.names=1)

# Show internal structure of the data
str(data, list.len=ncol(data), vec.len=nrow(data))
'data.frame':	25 obs. of  8 variables:
```

```
 $ SQ1: Factor w/ 4 levels "Kenne ich (schließt Nutzung aus)",..: 1 1 4 1 4 4 4 4 3 3 NA 3 3 1 2 3 4 1 NA 4 3 1 4 4 1
 $ SQ2: Factor w/ 4 levels "Kenne ich (schließt Nutzung aus)",..: 2 1 2 4 4 4 2 2 2 2 NA 4 2 2 2 4 4 2 NA 2 3 2 2 2 1
 $ SQ3: Factor w/ 4 levels "Kenne ich (schließt Nutzung aus)",..: 2 4 2 1 1 3 4 2 2 2 NA 3 2 2 4 4 4 1 NA 2 NA 1 2 4 1
 $ SQ4: Factor w/ 4 levels "Kenne ich (schließt Nutzung aus)",..: 3 3 4 4 1 4 4 2 2 3 NA 4 3 4 3 3 4 3 NA 2 NA 1 2 4 1
 $ SQ5: Factor w/ 3 levels "Kenne ich (schließt Nutzung aus)",..: 1 2 2 3 1 3 2 2 2 2 NA 3 2 2 2 3 3 2 NA 2 NA 2 3 2 2
 $ SQ6: Factor w/ 4 levels "Kenne ich (schließt Nutzung aus)",..: 1 2 2 4 4 4 1 2 2 3 NA 4 1 4 4 4 4 1 NA 4 NA 2 4 4 2
 $ SQ7: Factor w/ 3 levels "Kenne ich (schließt Nutzung aus)",..: 2 2 2 2 2 2 2 2 2 3 1 2 NA 2 2 2 2 2 NA 2 2 2 3 2 2
 $ Q3 : Factor w/ 2 levels "No","Yes": 2 2 2 2 2 2 NA NA 2 1 2 2 NA 2 2 1 1 2 2 1 NA 1 2 1 1
```

Listing 24: Question 5 – Setup (R dataset)

Descriptive Statistics

```
# Copy data
dataRefactored <- data
dataNumeric <- data

# Define levels
levels = c("Kenne ich nicht (schließt Nutzung aus)", "Kenne ich (schließt Nutzung aus)", "Nutze ich nicht (schließt Kenntnis ein)", "Nutze ich (schließt Kenntnis ein)")
levelsEnglish = c("Do not know (implicates non-usage)", "Know (implicates non-usage)", "Do not use (implicates knowledge)", "Use (implicates knowledge)")

# Rename responds
for(i in 1:(ncol(dataRefactored)-1)) {
    dataRefactored[[i]] = likert::recode(dataRefactored[[i]], from=levels, to=levelsEnglish)
}

# Replace columns with a factor
for(i in 1:(ncol(dataRefactored)-1)) {
    dataRefactored[[i]] = factor(dataRefactored[[i]], levels = levelsEnglish)
}

# Print descriptive statistics
summary(dataRefactored)
                                  SQ1
 Do not know (implicates non-usage):1
 Know (implicates non-usage)       :7
 Do not use (implicates knowledge) :9
```

```
Use (implicates knowledge)         :6
NA's                                :2

                                  SQ2
Do not know (implicates non-usage):14
Know (implicates non-usage)        : 2
Do not use (implicates knowledge) : 6
Use (implicates knowledge)         : 0
NA's                               : 3

                                  SQ3
Do not know (implicates non-usage):9
Know (implicates non-usage)        :5
Do not use (implicates knowledge) :6
Use (implicates knowledge)         :2
NA's                                :3

                                  SQ4
Do not know (implicates non-usage):4
Know (implicates non-usage)        :3
Do not use (implicates knowledge) :8
Use (implicates knowledge)         :7
NA's                               :3

                                  SQ5
Do not know (implicates non-usage):14
Know (implicates non-usage)        : 2
Do not use (implicates knowledge) : 6
Use (implicates knowledge)         : 0
NA's                                : 3

                                  SQ6
Do not know (implicates non-usage): 6
Know (implicates non-usage)        : 4
Do not use (implicates knowledge) :11
Use (implicates knowledge)         : 1
NA's                               : 3

                                  SQ7
Do not know (implicates non-usage): 0
Know (implicates non-usage)        : 1
Do not use (implicates knowledge) : 2
Use (implicates knowledge)         :20
NA's                                : 2

   Q3
No   : 7
Yes :14
NA's: 4

# dataNumeric: Rename responds
for(i in 1:(ncol(dataNumeric)-1)) {
```

```r
    dataNumeric[[i]] = likert::recode(dataNumeric[[i]], from=levels, to=c(1, 2, 3, 4))
}

# Print LaTeX table with descriptive statistics
stargazer::stargazer(dataNumeric, summary.stat = c("n", "mean", "sd", "min", "p25", "median", "p75", "max"))

# Print more detailed descriptive statistics (grouped by Q3; LaTeX table format)
dataNumeric$Q3 <- factor(dataNumeric$Q3, levels = c("Yes", "No"))

cat(paste("SQ", " & ",
          "Group", " & ",
          "N", " & ",
          "N (valid)", " & ",
          "Mean", " & ",
          "Std. Dev.", " & ",
          "Min", " & ",
          "Pctl(25)", " & ",
          "Median", " & ",
          "Pctl(75)", " & ",
          "Max",
          sep = ""
    ), sep = "\n"
)
cat("----------------------------------------------------------------------------------------", sep = "\n")

for (i in 1:(ncol(dataNumeric)-1)) {
  statistics <- FSA::Summarize(dataNumeric[[i]], digits=3, na.rm = TRUE, nvalid = "always", percZero = "always")
  statisticsGrouped <- FSA::Summarize(dataNumeric[[i]] ~ dataNumeric$Q3, digits=3, na.rm = TRUE, nvalid = "always", percZero = "always")

  sqindex <- paste("SQ", i, sep = "")

  cat(paste(sqindex, " & ",
            "Overall", " & ",
            statistics[[1]], " & ",
            statistics[[2]], " & ",
            statistics[[3]], " & ",
            statistics[[4]], " & ",
            statistics[[5]], " & ",
            statistics[[6]], " & ",
            statistics[[7]], " & ",
            statistics[[8]], " & ",
            statistics[[9]], "\\\\",
            sep=""),
      sep = "\n"
  )
```

```

  ws <- ""

  for (z in 1:nchar(sqindex)) {
    ws <- paste(ws, " ", sep = "")
  }

  for (j in 1:length(statisticsGrouped$dataNumeric$Q3)) {
    cat(paste(ws, " & ",
              statisticsGrouped$dataNumeric$Q3[[j]], " & ",
              statisticsGrouped$n[[j]], " & ",
              statisticsGrouped$nvalid[[j]], " & ",
              statisticsGrouped$mean[[j]], " & ",
              statisticsGrouped$sd[[j]], " & ",
              statisticsGrouped$min[[j]], " & ",
              statisticsGrouped$Q1[[j]], " & ",
              statisticsGrouped$median[[j]], " & ",
              statisticsGrouped$Q3[[j]], " & ",
              statisticsGrouped$max[[j]], "\\\\",
              sep=""),
        sep = "\n"
    )
  }

  cat(paste(ws, "\\hline"), sep = "\n")
}
```

Listing 25: Question 5 – Descriptive Statistics

Test for Normality

```
# Copy data
dataNumeric <- data

# Define levels
levels = c("Kenne ich nicht (schließt Nutzung aus)", "Kenne ich (schließt Nutzung aus)", "Nutze ich nicht (schließt Kenntnis ein)", "Nutze ich (schließt Kenntnis ein)")

# Rename responds
for(i in 1:(ncol(dataNumeric)-1)) {
    dataNumeric[[i]] = likert::recode(dataNumeric[[i]], from=levels, to=c(1, 2, 3, 4))
}

# Test each sub likert item of the question for normality
for(i in 1:(ncol(dataNumeric)-1)) {
    print(shapiro.test(dataNumeric[[i]]))
}

        Shapiro-Wilk normality test
```

```

data:  dataNumeric[[i]]
W = 0.86674, p-value = 0.005558


        Shapiro-Wilk normality test

data:  dataNumeric[[i]]
W = 0.64891, p-value = 4.682e-06


        Shapiro-Wilk normality test

data:  dataNumeric[[i]]
W = 0.83232, p-value = 0.001679


        Shapiro-Wilk normality test

data:  dataNumeric[[i]]
W = 0.8381, p-value = 0.002106


        Shapiro-Wilk normality test

data:  dataNumeric[[i]]
W = 0.64891, p-value = 4.682e-06


        Shapiro-Wilk normality test

data:  dataNumeric[[i]]
W = 0.80535, p-value = 0.0006075


        Shapiro-Wilk normality test

data:  dataNumeric[[i]]
W = 0.41164, p-value = 1.358e-08
```

Listing 26: Question 5 – Test for Normality

Test for Reliability (Cronbach Alpha)

```
# Copy data
dataNumeric <- data

# Define levels
levels = c("Kenne ich nicht (schließt Nutzung aus)", "Kenne ich
↪ (schließt Nutzung aus)", "Nutze ich nicht (schließt Kenntnis
↪ ein)", "Nutze ich (schließt Kenntnis ein)")
```

```

# Rename responds
for(i in 1:(ncol(dataNumeric)-1)) {
    dataNumeric[[i]] = likert::recode(dataNumeric[[i]], from=levels, to=c(1, 2, 3, 4))
}

# Run the alpha test only for columns data likert columns (i.e. without column Q3)
psych::alpha(dataNumeric[, c(1:(ncol(dataNumeric)-1))])

Reliability analysis
Call: psych::alpha(x = dataNumeric[, c(1:(ncol(dataNumeric) - 1))])

  raw_alpha std.alpha G6(smc) average_r S/N ase mean   sd
      0.64      0.61    0.71      0.18 1.6 0.1  2.5 0.59

 lower alpha upper     95% confidence boundaries
0.44 0.64 0.84

 Reliability if an item is dropped:
    raw_alpha std.alpha G6(smc) average_r  S/N alpha se
SQ1      0.68      0.66    0.74      0.24 1.92    0.092
SQ2      0.50      0.44    0.53      0.12 0.79    0.146
SQ3      0.53      0.49    0.61      0.14 0.97    0.137
SQ4      0.67      0.62    0.71      0.22 1.64    0.094
SQ5      0.53      0.49    0.57      0.14 0.94    0.136
SQ6      0.59      0.57    0.67      0.18 1.30    0.119
SQ7      0.67      0.68    0.75      0.26 2.13    0.101

 Item statistics
     n raw.r std.r r.cor  r.drop mean   sd
SQ1 23  0.37  0.32 0.105  0.0712  2.9 0.87
SQ2 22  0.82  0.81 0.879  0.6771  1.6 0.90
SQ3 22  0.76  0.72 0.700  0.5481  2.0 1.05
SQ4 22  0.45  0.43 0.263  0.1938  2.8 1.10
SQ5 22  0.76  0.74 0.776  0.5897  1.6 0.90
SQ6 22  0.62  0.57 0.476  0.4029  2.3 0.95
SQ7 23  0.20  0.24 0.037 -0.0072  3.8 0.49

Non missing response frequency for each item
       1    2    3    4 miss
SQ1 0.04 0.30 0.39 0.26 0.08
SQ2 0.64 0.09 0.27 0.00 0.12
SQ3 0.41 0.23 0.27 0.09 0.12
SQ4 0.18 0.14 0.36 0.32 0.12
SQ5 0.64 0.09 0.27 0.00 0.12
SQ6 0.27 0.18 0.50 0.05 0.12
SQ7 0.00 0.04 0.09 0.87 0.08
```

Listing 27: Question 5 – Test for Reliability (Cronbach Alpha)

Likert Statistics

```
# Load grid library needed for likert processing (at least in case of a Linux system)
library(grid)

# Define levels
levels = c("Kenne ich nicht (schließt Nutzung aus)", "Kenne ich (schließt Nutzung aus)", "Nutze ich nicht (schließt Kenntnis ein)", "Nutze ich (schließt Kenntnis ein)")
levelsEnglish = c("Do not know (implicates non-usage)", "Know (implicates non-usage)", "Do not use (implicates knowledge)", "Use (implicates knowledge)")

# Copy data
dataLikert <- data

# Rename responds
for(i in 1:(ncol(dataLikert)-1)) {
  dataLikert[[i]] = likert::recode(dataLikert[[i]], from=levels, to=levelsEnglish)
}

# Replace columns with an ordered factor
for(i in 1:(ncol(dataLikert)-1)) {
  dataLikert[[i]] = factor(dataLikert[[i]], levels = levelsEnglish)
}

# Rename columns
cols = c(
  "Scorecard Method",
  "Berkus Method",
  "Risk Factor Summation Method",
  "Venture Capital Method",
  "First Chicago Method",
  "Real Options Approach",
  "Experience"
)

for(i in 1:(ncol(dataLikert)-1)) {
  colnames(dataLikert)[i] <- cols[[i]]
}

# Show structure of the data
str(dataLikert)

'data.frame':	25 obs. of  8 variables:
 $ Scorecard Method            : Factor w/ 4 levels "Do not know (implicates non-usage)",..: 2 2 3 2 3 3 3 3 4 4 ...
 $ Berkus Method               : Factor w/ 4 levels "Do not know (implicates non-usage)",..: 1 2 1 3 3 3 1 1 1 1 ...
 $ Risk Factor Summation Method: Factor w/ 4 levels "Do not know (implicates non-usage)",..: 1 3 1 2 2 4 3 1 1 1 ...
```

```
 $ Venture Capital Method      : Factor w/ 4 levels "Do not know
 ↪  (implicates non-usage)",..: 4 4 3 3 2 3 3 1 1 4 ...
 $ First Chicago Method        : Factor w/ 4 levels "Do not know
 ↪  (implicates non-usage)",..: 2 1 1 3 2 3 1 1 1 1 ...
 $ Real Options Approach       : Factor w/ 4 levels "Do not know
 ↪  (implicates non-usage)",..: 2 1 1 3 3 3 2 1 1 4 ...
 $ Experience                  : Factor w/ 4 levels "Do not know
 ↪  (implicates non-usage)",..: 4 4 4 4 4 4 4 4 4 3 ...
 $ Q3                          : Factor w/ 2 levels "No","Yes": 2 2 2
 ↪  2 2 2 NA NA 2 1 ...

# Load fonts for postscript usage
extrafont::loadfonts(device="postscript")

# Plot likert (no histogram) to eps file
postscript(
  file = "./output/q5/q5q3-data-likert-plot-temp.eps",
  paper = "special",
  horizontal = FALSE,
  width = 10.15,
  height = 7.40,
  family = "Linux Libertine Display G",
  fonts = c("Linux Libertine Display G")
)
par(mar=c(0,0,0,0), las=1)
plot(likert::likert(dataLikert[, c(1:(ncol(dataLikert)-1))]),
↪  centered = TRUE, include.histogram = FALSE)
dev.off()

# Embed the designated font(s); device with/height points match eps
↪  with/height times 72
embedFonts(
  file = "./output/q5/q5q3-data-likert-plot-temp.eps",
  outfile = "./output/q5/q5q3-data-likert-plot.eps",
  fontpaths = "/usr/share/fonts/",
  options = "-dDEVICEWIDTHPOINTS=731 -dDEVICEHEIGHTPOINTS=533"
)

# Plot likert (with histogram) to eps file
postscript(
  file = "./output/q5/q5q3-data-likert-histogram-plot-temp.eps",
  paper = "special",
  horizontal = FALSE,
  width = 13.55,
  height = 9.85,
  family = "Linux Libertine Display G",
  fonts = c("Linux Libertine Display G")
)
par(mar=c(0,0,0,0), las=1)
plot(likert::likert(dataLikert[, c(1:(ncol(dataLikert)-1))]),
↪  centered = TRUE, include.histogram = TRUE)
dev.off()
```

```
# Embed the designated font(s); device with/height points match eps with/height times 72
embedFonts(
  file = "./output/q5/q5q3-data-likert-histogram-plot-temp.eps",
  outfile = "./output/q5/q5q3-data-likert-histogram-plot.eps",
  fontpaths = "/usr/share/fonts/",
  options = "-dDEVICEWIDTHPOINTS=976 -dDEVICEHEIGHTPOINTS=710"
)

# Plot likert (with histogram) to svg file
svg(
  file = "./output/q5/q5q3-data-likert-histogram-plot.svg",
  width = 13.55,
  height = 9.85,
  family = "Linux Libertine Display G"
)
par(mar=c(0,0,0,0), las=1)
plot(likert::likert(dataLikert[, c(1:(ncol(dataLikert)-1))]), centered = TRUE, include.histogram = TRUE)
dev.off()

# Plot likert (grouped by Q3; deleted NA answersets)
dataLikertGrouped <- na.omit(dataLikert)
plot(likert::likert(dataLikertGrouped[, c(1:(ncol(dataLikertGrouped)-1))], grouping = dataLikertGrouped$Q3), centered=TRUE, include.histogram = TRUE)
```

Listing 28: Question 5 – Likert Statistics

Wilcoxon Signed Rank Test

```
# Copy data
dataNumeric <- data

# Define levels
levels = c("Kenne ich nicht (schließt Nutzung aus)", "Kenne ich (schließt Nutzung aus)", "Nutze ich nicht (schließt Kenntnis ein)", "Nutze ich (schließt Kenntnis ein)")

# Rename responds
for(i in 1:(ncol(dataNumeric)-1)) {
    dataNumeric[[i]] = likert::recode(dataNumeric[[i]], from=levels, to=c(1, 2, 3, 4))
}

# Test whether the median of each sub likert question is significantly different from a hypothized median m = 1
for(i in 1:(ncol(dataNumeric)-1)) {
    print(wilcox.test(dataNumeric[[i]], mu=1, conf.int=TRUE, conf.level=0.95, alternative = "two.sided"))
}
```

```

         Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 253, p-value = 3.343e-05
alternative hypothesis: true location is not equal to 1
95 percent confidence interval:
 2.500058 3.499970
sample estimates:
(pseudo)median
      2.999989


         Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 36, p-value = 0.01028
alternative hypothesis: true location is not equal to 1
60 percent confidence interval:
 2.500003 3.000000
sample estimates:
(pseudo)median
      2.999932


         Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 91, p-value = 0.001374
alternative hypothesis: true location is not equal to 1
95 percent confidence interval:
 2.499969 3.000019
sample estimates:
(pseudo)median
      2.999989


         Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 171, p-value = 0.0001655
alternative hypothesis: true location is not equal to 1
95 percent confidence interval:
 2.999947 3.500024
sample estimates:
(pseudo)median
      3.000069


         Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 36, p-value = 0.01028
```

```
alternative hypothesis: true location is not equal to 1
60 percent confidence interval:
 2.500003 3.000000
sample estimates:
(pseudo)median
      2.999932


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 136, p-value = 0.0002804
alternative hypothesis: true location is not equal to 1
95 percent confidence interval:
 2.499978 3.000016
sample estimates:
(pseudo)median
      2.999962


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 276, p-value = 5.453e-06
alternative hypothesis: true location is not equal to 1
80 percent confidence interval:
 3.999942 4.000000
sample estimates:
(pseudo)median
             4


# Test whether the median of each sub likert question is
↪  significantly different from a hypothized median m = 2
for(i in 1:(ncol(dataNumeric)-1)) {
    print(wilcox.test(dataNumeric[[i]], mu=2, conf.int=TRUE,
    ↪  conf.level=0.95, alternative = "two.sided"))
}

        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 130.5, p-value = 0.0009041
alternative hypothesis: true location is not equal to 2
95 percent confidence interval:
 2.999928 3.500017
sample estimates:
(pseudo)median
      3.499953


        Wilcoxon signed rank test with continuity correction

```

```
data:  dataNumeric[[i]]
V = 63, p-value = 0.07713
alternative hypothesis: true location is not equal to 2
95 percent confidence interval:
 1.00000 2.00001
sample estimates:
(pseudo)median
      1.791288


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 81, p-value = 0.8366
alternative hypothesis: true location is not equal to 2
95 percent confidence interval:
 1.000083 2.999963
sample estimates:
(pseudo)median
      2.000002


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 164, p-value = 0.004273
alternative hypothesis: true location is not equal to 2
95 percent confidence interval:
 2.499962 3.500027
sample estimates:
(pseudo)median
      3.000037


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 63, p-value = 0.07713
alternative hypothesis: true location is not equal to 2
95 percent confidence interval:
 1.00000 2.00001
sample estimates:
(pseudo)median
      1.791288


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 117, p-value = 0.1328
alternative hypothesis: true location is not equal to 2
95 percent confidence interval:
 1.999951 3.000041
```

```
sample estimates:
(pseudo)median
      2.000018


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 253, p-value = 6.648e-06
alternative hypothesis: true location is not equal to 2
60 percent confidence interval:
 4 4
sample estimates:
(pseudo)median
             4


# Test whether the median of each sub likert question is significantly different from a hypothized median m = 3
for(i in 1:(ncol(dataNumeric)-1)) {
    print(wilcox.test(dataNumeric[[i]], mu=3, conf.int=TRUE, conf.level=0.95, alternative = "two.sided"))
}

        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 42, p-value = 0.4883
alternative hypothesis: true location is not equal to 3
95 percent confidence interval:
 1.999975 3.000046
sample estimates:
(pseudo)median
      2.999954


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 0, p-value = 0.0001499
alternative hypothesis: true location is not equal to 3
60 percent confidence interval:
 1.000000 1.000056
sample estimates:
(pseudo)median
             1


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 8, p-value = 0.001517
alternative hypothesis: true location is not equal to 3
```

```
95 percent confidence interval:
 1.00000 2.49995
sample estimates:
(pseudo)median
           1.5


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 38.5, p-value = 0.3753
alternative hypothesis: true location is not equal to 3
95 percent confidence interval:
 1.500052 4.000000
sample estimates:
(pseudo)median
       2.50005


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 0, p-value = 0.0001499
alternative hypothesis: true location is not equal to 3
60 percent confidence interval:
 1.000000 1.000056
sample estimates:
(pseudo)median
             1


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 3, p-value = 0.006993
alternative hypothesis: true location is not equal to 3
95 percent confidence interval:
 1.000000 2.499976
sample estimates:
(pseudo)median
      1.500052


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 220, p-value = 3.686e-05
alternative hypothesis: true location is not equal to 3
0 percent confidence interval:
 4 4
sample estimates:
(pseudo)median
             4
```

```


# Test whether the median of each sub likert question is
↪  significantly different from a hypothized median m = 4
for(i in 1:(ncol(dataNumeric)-1)) {
    print(wilcox.test(dataNumeric[[i]], mu=4, conf.int=TRUE,
    ↪  conf.level=0.95, alternative = "two.sided"))
}

        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 0, p-value = 0.0002244
alternative hypothesis: true location is not equal to 4
95 percent confidence interval:
 2.000012 2.999936
sample estimates:
(pseudo)median
      2.500015


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 0, p-value = 2.339e-05
alternative hypothesis: true location is not equal to 4
95 percent confidence interval:
 1.000000 2.000014
sample estimates:
(pseudo)median
      1.500074


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 0, p-value = 7.428e-05
alternative hypothesis: true location is not equal to 4
95 percent confidence interval:
 1.499959 2.000013
sample estimates:
(pseudo)median
      1.999976


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 0, p-value = 0.0005644
alternative hypothesis: true location is not equal to 4
95 percent confidence interval:
 1.999966 3.000000
sample estimates:
```

```
(pseudo)median
      2.116884


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 0, p-value = 2.339e-05
alternative hypothesis: true location is not equal to 4
95 percent confidence interval:
 1.000000 2.000014
sample estimates:
(pseudo)median
      1.500074


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 0, p-value = 4.511e-05
alternative hypothesis: true location is not equal to 4
95 percent confidence interval:
 1.999978 2.999947
sample estimates:
(pseudo)median
      2.000007


        Wilcoxon signed rank test with continuity correction

data:  dataNumeric[[i]]
V = 0, p-value = 0.1736
alternative hypothesis: true location is not equal to 4
0 percent confidence interval:
 3 3
sample estimates:
(pseudo)median
      2.585786
```

Listing 29: Question 5 – Wilcoxon Signed Rank Test

Fisher's Exact Test

```
# Copy data
dataFischer <- data

# Define levels
levels = c("Kenne ich nicht (schließt Nutzung aus)", "Kenne ich
↪  (schließt Nutzung aus)", "Nutze ich nicht (schließt Kenntnis
↪  ein)", "Nutze ich (schließt Kenntnis ein)")
```

```
levelsEnglish = c("Do not know (implicates non-usage)", "Know (implicates non-usage)", "Do not use (implicates knowledge)", "Use (implicates knowledge)")

# Rename responds
for(i in 1:(ncol(dataFischer)-1)) {
    dataFischer[[i]] = likert::recode(dataFischer[[i]], from=levels, to=levelsEnglish)
}

# Replace columns with an ordered factor
for(i in 1:(ncol(dataFischer)-1)) {
    dataFischer[[i]] = factor(dataFischer[[i]], levels = levelsEnglish)
}

# Recode Q3 in order for "Yes" being treated as the main response
dataFischer$Q3 <- factor(dataFischer$Q3, levels = c("Yes", "No"))

# Test whether the "No"/"Yes" groups differ
for(i in 1:(ncol(data)-1)) {
    print(fisher.test(table(dataFischer[[i]], dataFischer$Q3)))
}

        Fisher's Exact Test for Count Data

data:  table(dataFischer[[i]], dataFischer$Q3)
p-value = 0.9028
alternative hypothesis: two.sided


        Fisher's Exact Test for Count Data

data:  table(dataFischer[[i]], dataFischer$Q3)
p-value = 1
alternative hypothesis: two.sided


        Fisher's Exact Test for Count Data

data:  table(dataFischer[[i]], dataFischer$Q3)
p-value = 0.7083
alternative hypothesis: two.sided


        Fisher's Exact Test for Count Data

data:  table(dataFischer[[i]], dataFischer$Q3)
p-value = 0.8312
alternative hypothesis: two.sided


        Fisher's Exact Test for Count Data
```

```

data:  table(dataFischer[[i]], dataFischer$Q3)
p-value = 0.8035
alternative hypothesis: two.sided


        Fisher's Exact Test for Count Data

data:  table(dataFischer[[i]], dataFischer$Q3)
p-value = 0.6856
alternative hypothesis: two.sided


        Fisher's Exact Test for Count Data

data:  table(dataFischer[[i]], dataFischer$Q3)
p-value = 1
alternative hypothesis: two.sided
```

Listing 30: Question 5 – Fisher's Exact Test

B.6 Question 6: Which functionality should a platform for recommending early-stage enterprises to investors provide in order to offer additional value to you?

Dataset (Likert, ordinal scale 1-5 incl. no specification [NA])

Table B.6: Question 6: dataset (q6q3data.csv); original column names are shortened

Participant	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	Q3
p1	4	3	4	4	4	4	NA	NA	NA	NA	4	5	Yes
p2	2	2	4	4	4	3	4	4	4	3	4	3	Yes
p3	2	4	4	4	3	2	3	1	4	2	1	2	Yes
p4	3	4	3	4	5	4	5	4	3	3	4	5	Yes
p5	5	2	5	4	4	2	3	3	3	2	4	4	Yes
p6	5	4	5	5	5	5	5	3	5	3	3	4	Yes
p7	5	3	3	4	4	3	5	4	4	1	1	4	NA
p8	4	3	2	4	5	4	4	3	4	2	4	4	NA
p9	5	5	3	3	5	5	5	5	5	1	5	5	Yes
p10	5	4	2	2	5	5	5	2	5	2	4	5	No
p11	2	2	2	3	2	2	3	3	2	2	2	2	Yes

To be continued on next page…

. . . continued from previous page

p12	3	4	3	3	3	4	2	4	5	4	4	3	Yes
p13	5	5	4	3	5	4	4	3	5	3	3	5	NA
p14	4	3	4	2	2	2	5	3	3	2	3	4	Yes
p15	3	2	4	4	4	1	2	1	4	NA	4	1	Yes
p16	5	3	5	3	5	3	3	1	5	5	1	3	No
p17	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	No
p18	5	5	5	5	5	4	5	3	5	2	5	3	Yes
p19	5	3	4	3	5	3	3	2	4	3	4	5	Yes
p20	2	1	3	1	2	2	3	3	3	1	2	2	No
p21	4	4	4	4	5	3	4	4	5	2	2	4	NA
p22	5	2	2	2	5	4	4	4	5	3	2	3	No
p23	2	2	2	2	2	2	2	3	3	2	2	2	Yes
p24	4	3	3	3	3	4	5	4	5	3	4	3	No
p25	1	5	2	2	1	3	2	5	1	4	2	3	No

Setup (R dataset)

```
# Read data from CSV
data <- read.csv("q6q3data.csv", row.names=1)

# Show internal structure of the data
str(data, list.len=ncol(data), vec.len=nrow(data))
'data.frame':       25 obs. of  10 variables:
 $ SQ1 : int  4 2 2 3 5 5 5 4 5 5 2 3 5 4 3 5 NA 5 5 2 4 5 2 4 1
 $ SQ2 : int  3 2 4 4 2 4 3 3 5 4 2 4 5 3 2 3 NA 5 3 1 4 2 2 3 5
 $ SQ3 : int  4 4 4 3 5 5 3 2 3 2 2 3 4 4 4 5 NA 5 4 3 4 2 2 3 2
 $ SQ4 : int  4 4 4 4 4 5 4 4 3 2 3 3 3 2 4 3 NA 5 3 1 4 2 2 3 2
 $ SQ5 : int  4 4 3 5 4 5 4 5 5 5 2 3 5 2 4 5 NA 5 5 2 5 5 2 3 1
 $ SQ6 : int  4 3 2 4 2 5 3 4 5 5 2 4 4 2 1 3 NA 4 3 2 3 4 2 4 3
 $ SQ7 : int  NA 4 3 5 3 5 5 4 5 5 3 2 4 5 2 3 NA 5 3 3 4 4 2 5 2
 $ SQ8 : int  NA 4 1 4 3 3 4 3 5 2 3 4 3 3 1 1 NA 3 2 3 4 4 3 4 5
 $ SQ9 : int  NA 4 4 3 3 5 4 4 5 5 2 5 5 3 4 5 NA 5 4 3 5 5 3 5 1
 $ SQ10: int  NA 3 2 3 2 3 1 2 1 2 2 4 3 2 NA 5 NA 2 3 1 2 3 2 3 4
 $ SQ11: int  4 4 1 4 4 3 1 4 5 4 2 4 3 3 4 1 NA 5 4 2 2 2 2 4 2
 $ SQ12: int  5 3 2 5 4 4 4 4 5 5 2 3 5 4 1 3 NA 3 5 2 4 3 2 3 3
 $ Q3  : Factor w/ 2 levels "No","Yes": 2 2 2 2 2 2 NA NA 2 1 2 2 NA
 ↪  2 2 1 1 2 2 1 NA 1 2 1 1
```

Listing 31: Question 6 – Setup (R dataset)

Descriptive Statistics

```r
# Print LaTeX table with descriptive statistics
stargazer::stargazer(data, summary.stat = c("n", "mean", "sd", "min", "p25", "median", "p75", "max"))

# Print more detailed descriptive statistics (grouped by Q3; LaTeX table format)
data$Q3 <- factor(data$Q3, levels = c("Yes", "No"))

cat(paste("SQ", " & ",
          "Group", " & ",
          "N", " & ",
          "N (valid)", " & ",
          "Mean", " & ",
          "Std. Dev.", " & ",
          "Min", " & ",
          "Pctl(25)", " & ",
          "Median", " & ",
          "Pctl(75)", " & ",
          "Max",
          sep = ""
    ), sep = "\n"
)
cat("-----------------------------------------------------------------------------------------", sep = "\n")

for (i in 1:(ncol(data)-1)) {
  statistics <- FSA::Summarize(data[[i]], digits=3, na.rm = TRUE, nvalid = "always", percZero = "always")
  statisticsGrouped <- FSA::Summarize(data[[i]] ~ data$Q3, digits=3, na.rm = TRUE, nvalid = "always", percZero = "always")

  sqindex <- paste("SQ", i, sep = "")

  cat(paste(sqindex, " & ",
            "Overall", " & ",
            statistics[[1]], " & ",
            statistics[[2]], " & ",
            statistics[[3]], " & ",
            statistics[[4]], " & ",
            statistics[[5]], " & ",
            statistics[[6]], " & ",
            statistics[[7]], " & ",
            statistics[[8]], " & ",
            statistics[[9]], "\\\\",
            sep=""),
      sep = "\n"
  )

  ws <- ""

```

```
  for (z in 1:nchar(sqindex)) {
    ws <- paste(ws, " ", sep = "")
  }

  for (j in 1:length(statisticsGrouped$data$Q3)) {
    cat(paste(ws, " & ",
              statisticsGrouped$data$Q3[[j]], " & ",
              statisticsGrouped$n[[j]], " & ",
              statisticsGrouped$nvalid[[j]], " & ",
              statisticsGrouped$mean[[j]], " & ",
              statisticsGrouped$sd[[j]], " & ",
              statisticsGrouped$min[[j]], " & ",
              statisticsGrouped$Q1[[j]], " & ",
              statisticsGrouped$median[[j]], " & ",
              statisticsGrouped$Q3[[j]], " & ",
              statisticsGrouped$max[[j]], "\\\\",
              sep=""),
        sep = "\n"
    )
  }

  cat(paste(ws, "\\hline"), sep = "\n")
}
```

Listing 32: Question 6 – Descriptive Statistics

Test for Normality

```
# Test each sub likert item of the question for normality
for(i in 1:(ncol(data)-1)) {
    print(shapiro.test(data[[i]]))
}

        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.82701, p-value = 0.0008424


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.91389, p-value = 0.04287


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.87352, p-value = 0.006172


```

```
        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.9085, p-value = 0.03273


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.80959, p-value = 0.0004245


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.91169, p-value = 0.03837


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.84686, p-value = 0.002388


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.8933, p-value = 0.01844


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.82216, p-value = 0.0008864


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.89636, p-value = 0.02515


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.87427, p-value = 0.006385


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.904, p-value = 0.02619
```

Listing 33: Question 6 – Test for Normality

Test for Reliability (Cronbach Alpha)

```
# Run the alpha test only for columns data likert columns (i.e.
↪ without column Q3)
psych::alpha(data[, c(1:(ncol(data) - 1))])

Reliability analysis
Call: psych::alpha(x = data[, c(1:(ncol(data) - 1))])

  raw_alpha std.alpha G6(smc) average_r S/N   ase mean   sd
      0.83      0.82    0.92      0.27 4.5 0.049  3.4 0.68

 lower alpha upper     95% confidence boundaries
0.73 0.83 0.92

 Reliability if an item is dropped:
     raw_alpha std.alpha G6(smc) average_r S/N alpha se
SQ1       0.79      0.79    0.90      0.25 3.7    0.059
SQ2       0.81      0.80    0.91      0.27 4.0    0.052
SQ3       0.83      0.82    0.90      0.29 4.6    0.048
SQ4       0.82      0.81    0.90      0.28 4.2    0.051
SQ5       0.79      0.78    0.89      0.25 3.6    0.060
SQ6       0.79      0.78    0.88      0.24 3.6    0.059
SQ7       0.80      0.79    0.90      0.26 3.9    0.056
SQ8       0.84      0.84    0.92      0.32 5.2    0.044
SQ9       0.80      0.79    0.89      0.26 3.8    0.056
SQ10      0.85      0.84    0.92      0.33 5.3    0.044
SQ11      0.82      0.81    0.92      0.28 4.2    0.051
SQ12      0.80      0.79    0.89      0.25 3.7    0.057

 Item statistics
      n raw.r std.r r.cor r.drop mean  sd
SQ1  24  0.76  0.75 0.749 0.6820  3.8 1.3
SQ2  24  0.60  0.62 0.568 0.5049  3.2 1.2
SQ3  24  0.40  0.41 0.387 0.2804  3.4 1.1
SQ4  24  0.53  0.54 0.508 0.4219  3.2 1.0
SQ5  24  0.80  0.80 0.812 0.7417  3.9 1.3
SQ6  24  0.80  0.81 0.825 0.7524  3.2 1.1
SQ7  23  0.69  0.68 0.663 0.6029  3.7 1.1
SQ8  23  0.20  0.21 0.139 0.0682  3.1 1.1
SQ9  23  0.70  0.70 0.705 0.6233  4.0 1.1
SQ10 22  0.13  0.15 0.085 0.0029  2.5 1.0
SQ11 24  0.56  0.54 0.462 0.4284  3.1 1.2
SQ12 24  0.75  0.73 0.731 0.6632  3.5 1.2

Non missing response frequency for each item
        1    2    3    4    5 miss
SQ1  0.04 0.21 0.12 0.21 0.42 0.04
SQ2  0.04 0.25 0.29 0.25 0.17 0.04
SQ3  0.00 0.25 0.25 0.33 0.17 0.04
```

```
SQ4  0.04 0.21 0.29 0.38 0.08 0.04
SQ5  0.04 0.17 0.12 0.21 0.46 0.04
SQ6  0.04 0.25 0.25 0.33 0.12 0.04
SQ7  0.00 0.17 0.26 0.22 0.35 0.08
SQ8  0.13 0.09 0.39 0.30 0.09 0.08
SQ9  0.04 0.04 0.22 0.26 0.43 0.08
SQ10 0.14 0.41 0.32 0.09 0.05 0.12
SQ11 0.12 0.25 0.12 0.42 0.08 0.04
SQ12 0.04 0.17 0.29 0.25 0.25 0.04
```

Listing 34: Question 6 – Test for Reliability (Cronbach Alpha)

Likert Statistics

```
# Load grid library needed for likert processing (at least in case of a Linux system)
library(grid)

# Define levels
levels = c("Unimportant", "Rather unimportant", "Neutral", "Rather important", "Important")

# Copy data
dataLikert <- data

# Rename responds
for(i in 1:(ncol(dataLikert)-1)) {
    dataLikert[[i]] = likert::recode(dataLikert[[i]], from=c(1, 2, 3, 4, 5), to=levels)
}

# Replace columns with an ordered factor
for(i in 1:(ncol(dataLikert)-1)) {
    dataLikert[[i]] = factor(dataLikert[[i]], levels = levels, ordered = TRUE)
}

# Rename columns
cols = c(
    "Visualization of detailed data concerning early-stage enterprises (private area)",
    "Public profile of early-stage enterprises (for measuring customer acceptance)",
    "Investment profile for investors (favourite industry sectors, product interests, investment amount, ...)",
    "Straightforward setup assistant for configuring the investment profile",
    "Filtering early-stage enterprises according to personal preferences",
    "Highlighting of popular early-stage enterprises (high public/investor interest)",
```

```
    "Visualization of pre-money valuations of early-stage
    ↪  enterprises",
    "Visualization of investment amount vs. risk",
    "Visualization of the founder team's experience",
    "Smartphone application",
    "E-Mail / Push notification at availability of new interesting
    ↪  early-stage enterprises",
    "Anonymity to visitors of the platform (visitors are neither
    ↪  investors, nor innovators)"
)

for(i in 1:(ncol(dataLikert)-1)) {
    colnames(dataLikert)[i] <- cols[[i]]
}

# Show structure of the data
str(dataLikert)
'data.frame':        25 obs. of  13 variables:
 $ Visualization of detailed data concerning early-stage enterprises
 ↪  (private area)                          : Ord.factor w/ 5 levels
 ↪  "Unimportant"<..: 4 2 2 3 5 5 5 4 5 5 ...
 $ Public profile of early-stage enterprises (for measuring customer
 ↪  acceptance)                             : Ord.factor w/ 5 levels
 ↪  "Unimportant"<..: 3 2 4 4 2 4 3 3 5 4 ...
 $ Investment profile for investors (favourite industry sectors,
 ↪  product interests, investment amount, ...): Ord.factor w/ 5
 ↪  levels "Unimportant"<..: 4 4 4 3 5 5 3 2 3 2 ...
 $ Straightforward setup assistant for configuring the investment
 ↪  profile                                   : Ord.factor w/ 5 levels
 ↪  "Unimportant"<..: 4 4 4 4 4 5 4 4 3 2 ...
 $ Filtering early-stage enterprises according to personal
 ↪  preferences                                    : Ord.factor w/ 5
 ↪  levels "Unimportant"<..: 4 4 3 5 4 5 4 5 5 5 ...
 $ Highlighting of popular early-stage enterprises (high
 ↪  public/investor interest)                         : Ord.factor w/
 ↪  5 levels "Unimportant"<..: 4 3 2 4 2 5 3 4 5 5 ...
 $ Visualization of pre-money valuations of early-stage enterprises
 ↪  : Ord.factor w/ 5 levels "Unimportant"<..: NA 4 3 5 3 5 5 4 5 5
 ↪  ...
 $ Visualization of investment amount vs. risk
 ↪  : Ord.factor w/ 5 levels "Unimportant"<..: NA 4 1 4 3 3 4 3 5 2
 ↪  ...
 $ Visualization of the founder teams experience
 ↪  : Ord.factor w/ 5 levels "Unimportant"<..: NA 4 4 3 3 5 4 4 5 5
 ↪  ...
 $ Smartphone application
 ↪  : Ord.factor w/ 5 levels "Unimportant"<..: NA 3 2 3 2 3 1 2 1 2
 ↪  ...
 $ E-Mail / Push notification at availability of new interesting
 ↪  early-stage enterprises                     : Ord.factor w/ 5
 ↪  levels "Unimportant"<..: 4 4 1 4 4 3 1 4 5 4 ...
```

```
 $ Anonymity to visitors of the platform (visitors are neither
 ↪  investors, nor innovators)                  : Ord.factor w/ 5
 ↪  levels "Unimportant"<..: 5 3 2 5 4 4 4 4 5 5 ...
 $ Q3
 ↪  : Factor w/ 2 levels "No","Yes": 2 2 2 2 2 2 NA NA 2 1 ...

# Load fonts for postscript usage
extrafont::loadfonts(device="postscript")

# Plot likert (no histogram) to eps file
postscript(
  file = "./output/q6/q6q3-data-likert-plot-temp.eps",
  paper = "special",
  horizontal = FALSE,
  width = 8.30,
  height = 6.00,
  family = "Linux Libertine Display G",
  fonts = c("Linux Libertine Display G")
)
par(mar=c(0,0,0,0), las=1)
plot(likert::likert(dataLikert[, c(1:(ncol(dataLikert)-1))]),
↪  centered = TRUE, include.histogram = FALSE)
dev.off()

# Embed the designated font(s); device with/height points match eps
↪  with/height times 72
embedFonts(
  file = "./output/q6/q6q3-data-likert-plot-temp.eps",
  outfile = "./output/q6/q6q3-data-likert-plot.eps",
  fontpaths = "/usr/share/fonts/",
  options = "-dDEVICEWIDTHPOINTS=598 -dDEVICEHEIGHTPOINTS=432"
)

# Plot likert (with histogram) to eps file
postscript(
  file = "./output/q6/q6q3-data-likert-histogram-plot-temp.eps",
  paper = "special",
  horizontal = FALSE,
  width = 11.00,
  height = 7.95,
  family = "Linux Libertine Display G",
  fonts = c("Linux Libertine Display G")
)
par(mar=c(0,0,0,0), las=1)
plot(likert::likert(dataLikert[, c(1:(ncol(dataLikert)-1))]),
↪  centered = TRUE,include.histogram = TRUE)
dev.off()

# Embed the designated font(s); device with/height points match eps
↪  with/height times 72
embedFonts(
  file = "./output/q6/q6q3-data-likert-histogram-plot-temp.eps",
  outfile = "./output/q6/q6q3-data-likert-histogram-plot.eps",
```

```
  fontpaths = "/usr/share/fonts/",
  options = "-dDEVICEWIDTHPOINTS=792 -dDEVICEHEIGHTPOINTS=573"

# Plot likert (grouped by Q3; deleted NA answersets)
dataLikertGrouped <- na.omit(dataLikert)
plot(likert::likert(dataLikertGrouped[,
↪  c(1:(ncol(dataLikertGrouped)-1))], grouping =
↪  dataLikertGrouped$Q3), centered=TRUE, include.histogram = TRUE)
```

Listing 35: Question 6 – Likert Statistics

Wilcoxon Signed Rank Test

```
# Test whether the median of each sub likert question is
↪  significantly greater than a hypothized median m = 3
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]], mu=3, conf.int=TRUE,
    ↪  conf.level=0.95, alternative = "greater"))
}

        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 187.5, p-value = 0.005223
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.499976      Inf
sample estimates:
(pseudo)median
             4


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 99, p-value = 0.138
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 2.999924      Inf
sample estimates:
(pseudo)median
      3.499981


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 126, p-value = 0.03239
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.000025      Inf
```

```
sample estimates:
(pseudo)median
      3.500003


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 99.5, p-value = 0.1269
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 2.999948       Inf
sample estimates:
(pseudo)median
      3.000046


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 195.5, p-value = 0.002172
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.499939       Inf
sample estimates:
(pseudo)median
      4.499906


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 109.5, p-value = 0.139
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 2.999967       Inf
sample estimates:
(pseudo)median
      3.000037


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 133, p-value = 0.003166
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.499935       Inf
sample estimates:
(pseudo)median
      4.000048
```

```
         Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 59, p-value = 0.3481
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 2.500031      Inf
sample estimates:
(pseudo)median
      3.000086


         Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 154, p-value = 0.001094
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 4.00002      Inf
sample estimates:
(pseudo)median
      4.499989


         Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 25.5, p-value = 0.9816
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 1.500029      Inf
sample estimates:
(pseudo)median
      2.000002


         Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 123, p-value = 0.3985
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 2.500009      Inf
sample estimates:
(pseudo)median
      3.000016


         Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 117, p-value = 0.02529
alternative hypothesis: true location is greater than 3
```

```
95 percent confidence interval:
 3.000066       Inf
sample estimates:
(pseudo)median
      3.999954
```

Listing 36: Question 6 – Wilcoxon Signed Rank Test

Wilcoxon Rank Sum Test

```
# Recode Q3 in order for "Yes" being treated as the main response
data$Q3 <- factor(data$Q3, levels = c("Yes", "No"))

# Test whether the location shift for the "No" group to the "Yes"
↪  group is different to 0
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]] ~ Q3, data = data, alternative =
    ↪  "two.sided"))
}

        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 39.5, p-value = 0.8631
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 45.5, p-value = 0.7986
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 61.5, p-value = 0.1053
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 73, p-value = 0.009152
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
```

```
W = 44, p-value = 0.8973
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 33.5, p-value = 0.4954
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 38, p-value = 0.9633
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 35, p-value = 0.75
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 31, p-value = 0.4881
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 26, p-value = 0.3494
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 60.5, p-value = 0.1161
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 47.5, p-value = 0.6693
alternative hypothesis: true location shift is not equal to 0
```

```
# Test whether the location shift for the "No" group to the "Yes"
↪  group is less than 0
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]] ~ Q3, data = data, alternative =
    ↪  "less"))
}

        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 39.5, p-value = 0.4316
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 45.5, p-value = 0.6331
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 61.5, p-value = 0.9559
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 73, p-value = 0.9964
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 44, p-value = 0.5852
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 33.5, p-value = 0.2477
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 38, p-value = 0.4817
```

```
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 35, p-value = 0.375
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 31, p-value = 0.244
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 26, p-value = 0.1747
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 60.5, p-value = 0.9514
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 47.5, p-value = 0.6959
alternative hypothesis: true location shift is less than 0


# Test whether the location shift for the "No" group to the "Yes" group is greater than 0
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]] ~ Q3, data = data, alternative = "greater"))
}

        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 39.5, p-value = 0.602
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction
```

```

data:  data[[i]] by Q3
W = 45.5, p-value = 0.3993
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 61.5, p-value = 0.05265
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 73, p-value = 0.004576
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 44, p-value = 0.4487
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 33.5, p-value = 0.7784
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 38, p-value = 0.5548
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 35, p-value = 0.659
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 31, p-value = 0.784
alternative hypothesis: true location shift is greater than 0
```

```


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 26, p-value = 0.8495
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 60.5, p-value = 0.05803
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 47.5, p-value = 0.3347
alternative hypothesis: true location shift is greater than 0
```

Listing 37: Question 6 – Wilcoxon Rank Sum Test

B.7 Question 7: According to which criteria shall recommendations be generated?

Dataset (Likert, ordinal scale 1-5 incl. no specification [NA])

Table B.7: Question 7: dataset (q7q3data.csv)

Participant	SQ1	SQ2	SQ3	SQ4	SQ5	SQ6	Q3
p1	4	4	4	4	NA	NA	Yes
p2	4	5	5	4	3	3	Yes
p3	2	3	2	2	1	2	Yes
p4	4	4	3	4	4	2	Yes
p5	2	5	3	5	3	2	Yes
p6	4	3	3	4	3	4	Yes
p7	NA	3	3	4	3	3	NA
p8	4	4	5	4	2	4	NA
p9	5	1	1	3	5	4	Yes
p10	3	4	3	5	5	4	No

To be continued on next page…

... continued from previous page

p11	2	2	2	2	2	3	Yes
p12	2	2	2	3	3	3	Yes
p13	4	4	4	4	4	4	NA
p14	3	3	3	3	3	3	Yes
p15	3	4	4	4	1	1	Yes
p16	1	4	3	5	1	1	No
p17	NA	NA	NA	NA	NA	NA	No
p18	2	5	4	5	2	2	Yes
p19	2	4	4	5	3	3	Yes
p20	2	3	4	3	2	2	No
p21	2	4	2	5	2	2	NA
p22	2	5	2	4	4	4	No
p23	NA	NA	NA	NA	NA	NA	Yes
p24	2	4	4	5	2	3	No
p25	2	4	1	2	5	3	No

Setup (R dataset)

```
# Read data from CSV
data <- read.csv("q7q3data.csv", row.names=1)

# Show internal structure of the data
str(data, list.len=ncol(data), vec.len=nrow(data))
'data.frame':        25 obs. of  7 variables:
 $ SQ1: int  4 4 2 4 2 4 NA 4 5 3 2 2 4 3 3 1 NA 2 2 2 2 2 NA 2 2
 $ SQ2: int  4 5 3 4 5 3 3 4 1 4 2 2 4 3 4 4 NA 5 4 3 4 5 NA 4 4
 $ SQ3: int  4 5 2 3 3 3 3 5 1 3 2 2 4 3 4 3 NA 4 4 4 2 2 NA 4 1
 $ SQ4: int  4 4 2 4 5 4 4 4 3 5 2 3 4 3 4 5 NA 5 5 3 5 4 NA 5 2
 $ SQ5: int  NA 3 1 4 3 3 3 2 5 5 2 3 4 3 1 1 NA 2 3 2 2 4 NA 2 5
 $ SQ6: int  NA 3 2 2 2 4 3 4 4 4 3 3 4 3 1 1 NA 2 3 2 2 4 NA 3 3
 $ Q3 : Factor w/ 2 levels "No","Yes": 2 2 2 2 2 2 NA NA 2 1 2 2 NA 2
 ↪  2 1 1 2 2 1 NA 1 2 1 1
```

Listing 38: Question 7 – Setup (R dataset)

Descriptive Statistics

```
# Print LaTeX table with descriptive statistics
stargazer::stargazer(data, summary.stat = c("n", "mean", "sd", "min",
↪  "p25", "median", "p75", "max"))

```

```
# Print more detailed descriptive statistics (grouped by Q3; LaTeX table format)
data$Q3 <- factor(data$Q3, levels = c("Yes", "No"))

cat(paste("SQ", " & ",
          "Group", " & ",
          "N", " & ",
          "N (valid)", " & ",
          "Mean", " & ",
          "Std. Dev.", " & ",
          "Min", " & ",
          "Pctl(25)", " & ",
          "Median", " & ",
          "Pctl(75)", " & ",
          "Max",
          sep = ""
    ), sep = "\n"
)
cat("----------------------------------------------------------------------------------------", sep = "\n")

for (i in 1:(ncol(data)-1)) {
  statistics <- FSA::Summarize(data[[i]], digits=3, na.rm = TRUE, nvalid = "always", percZero = "always")
  statisticsGrouped <- FSA::Summarize(data[[i]] ~ data$Q3, digits=3, na.rm = TRUE, nvalid = "always", percZero = "always")

  sqindex <- paste("SQ", i, sep = "")

  cat(paste(sqindex, " & ",
            "Overall", " & ",
            statistics[[1]], " & ",
            statistics[[2]], " & ",
            statistics[[3]], " & ",
            statistics[[4]], " & ",
            statistics[[5]], " & ",
            statistics[[6]], " & ",
            statistics[[7]], " & ",
            statistics[[8]], " & ",
            statistics[[9]], "\\\\",
            sep=""),
      sep = "\n"
  )

  ws <- ""

  for (z in 1:nchar(sqindex)) {
    ws <- paste(ws, " ", sep = "")
  }

  for (j in 1:length(statisticsGrouped$data$Q3)) {
    cat(paste(ws, " & ",
```

```
                  statisticsGrouped$data$Q3[[j]], " & ",
                  statisticsGrouped$n[[j]], " & ",
                  statisticsGrouped$nvalid[[j]], " & ",
                  statisticsGrouped$mean[[j]], " & ",
                  statisticsGrouped$sd[[j]], " & ",
                  statisticsGrouped$min[[j]], " & ",
                  statisticsGrouped$Q1[[j]], " & ",
                  statisticsGrouped$median[[j]], " & ",
                  statisticsGrouped$Q3[[j]], " & ",
                  statisticsGrouped$max[[j]], "\\\\",
                  sep=""),
            sep = "\n"
        )
    }

    cat(paste(ws, "\\hline"), sep = "\n")
}
```

Listing 39: Question 7 – Descriptive Statistics

Test for Normality

```
# Test each sub likert item of the question for normality
for(i in 1:(ncol(data)-1)) {
    print(shapiro.test(data[[i]]))
}

        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.83453, p-value = 0.00183


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.86923, p-value = 0.006196


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.92281, p-value = 0.07652


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.85268, p-value = 0.003043


```

```
        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.91394, p-value = 0.05701


        Shapiro-Wilk normality test

data:  data[[i]]
W = 0.87539, p-value = 0.009876
```

Listing 40: Question 7 – Test for Normality

Test for Reliability (Cronbach Alpha)

```
# Run the alpha test only for columns data likert columns (i.e.
↪ without column Q3)
psych::alpha(data[, c(1:(ncol(data) - 1))])

Some items ( SQ2 SQ3 SQ4 ) were negatively correlated with the total
↪ scale and
probably should be reversed.
To do this, run the function again with the 'check.keys=TRUE' option
Reliability analysis
Call: psych::alpha(x = data[, c(1:(ncol(data) - 1))])

  raw_alpha std.alpha G6(smc) average_r S/N  ase mean   sd
       0.5      0.51    0.77      0.15   1 0.17  3.2 0.59

 lower alpha upper     95% confidence boundaries
0.18 0.5 0.83

 Reliability if an item is dropped:
    raw_alpha std.alpha G6(smc) average_r  S/N alpha se
SQ1      0.41      0.43    0.68      0.13 0.74     0.20
SQ2      0.48      0.49    0.70      0.16 0.96     0.17
SQ3      0.47      0.46    0.63      0.15 0.86     0.17
SQ4      0.44      0.45    0.75      0.14 0.83     0.19
SQ5      0.51      0.50    0.65      0.17 0.99     0.16
SQ6      0.43      0.46    0.72      0.15 0.85     0.19

 Item statistics
     n raw.r std.r r.cor r.drop mean   sd
SQ1 22  0.61  0.60  0.53   0.36  2.8 1.07
SQ2 23  0.49  0.50  0.43   0.21  3.7 1.03
SQ3 23  0.55  0.54  0.51   0.23  3.1 1.12
SQ4 23  0.54  0.56  0.44   0.28  3.9 1.01
SQ5 22  0.51  0.49  0.46   0.18  2.9 1.25
SQ6 22  0.55  0.55  0.47   0.31  2.8 0.96

Non missing response frequency for each item
```

```
        1    2    3    4    5 miss
SQ1 0.05 0.50 0.14 0.27 0.05 0.12
SQ2 0.04 0.09 0.22 0.48 0.17 0.08
SQ3 0.09 0.22 0.30 0.30 0.09 0.08
SQ4 0.00 0.13 0.17 0.39 0.30 0.08
SQ5 0.14 0.27 0.32 0.14 0.14 0.12
SQ6 0.09 0.27 0.36 0.27 0.00 0.12
Warning message:
In psych::alpha(data[, c(1:(ncol(data) - 1))]) :
  Some items were negatively correlated with the total scale and probably
should be reversed.
To do this, run the function again with the 'check.keys=TRUE' option
```

Listing 41: Question 7 – Test for Reliability (Cronbach Alpha)

Likert Statistics

```
# Load grid library needed for likert processing (at least in case of a Linux system)
library(grid)

# Define levels
levels = c("Unimportant", "Rather unimportant", "Neutral", "Rather important", "Important")

# Copy data
dataLikert <- data

# Rename responds
for(i in 1:(ncol(dataLikert)-1)) {
    dataLikert[[i]] = likert::recode(dataLikert[[i]], from=c(1, 2, 3, 4, 5), to=levels)
}

# Replace columns with an ordered factor
for(i in 1:(ncol(dataLikert)-1)) {
    dataLikert[[i]] = factor(dataLikert[[i]], levels = levels, ordered = TRUE)
}

# Rename columns
cols = c(
    "Include early-stage enterprise recommendations that do not match your investor's profile",
    "Recommendations based on your former investment decisions",
    "Recommendations based on the investments or interests of other (certain) investors",
    "Recommendations based on an investor's profile",
    "Recommendations based on balancing your investment portfolio (risk vs. revenue)",
```

```
    "Recommendations based on the pre-money valuation of early-stage
    ↪ enterprises"
)

for(i in 1:(ncol(dataLikert)-1)) {
    colnames(dataLikert)[i] <- cols[[i]]
}

# Show structure of the data
str(dataLikert)
'data.frame':       25 obs. of  7 variables:
 $ Include early-stage enterprise recommendations that do not match
  ↪  your investor's profile: Ord.factor w/ 5 levels
  ↪  "Unimportant"<..: 4 4 2 4 2 4 NA 4 5 3 ...
 $ Recommendations based on your former investment decisions
 ↪  : Ord.factor w/ 5 levels "Unimportant"<..: 4 5 3 4 5 3 3 4 1 4 ...
 $ Recommendations based on the investments or interests of other
 ↪  (certain) investors      : Ord.factor w/ 5 levels
 ↪  "Unimportant"<..: 4 5 2 3 3 3 3 5 1 3 ...
 $ Recommendations based on an investor's profile
 ↪  : Ord.factor w/ 5 levels "Unimportant"<..: 4 4 2 4 5 4 4 4 3 5 ...
 $ Recommendations based on balancing your investment portfolio (risk
  ↪  vs. revenue)         : Ord.factor w/ 5 levels "Unimportant"<..:
  ↪  NA 3 1 4 3 3 3 2 5 5 ...
 $ Recommendations based on the pre-money valuation of early-stage
  ↪  enterprises              : Ord.factor w/ 5 levels
  ↪  "Unimportant"<..: NA 3 2 2 2 4 3 4 4 4 ...
 $ Q3
  ↪  : Factor w/ 2 levels "No","Yes": 2 2 2 2 2 2 NA NA 2 1 ...

# Load fonts for postscript usage
extrafont::loadfonts(device="postscript")

# Plot likert (no histogram) to eps file
postscript(
  file = "./output/q7/q7q3-data-likert-plot-temp.eps",
  paper = "special",
  horizontal = FALSE,
  width = 8.70,
  height = 6.29,
  family = "Linux Libertine Display G",
  fonts = c("Linux Libertine Display G")
)
par(mar=c(0,0,0,0), las=1)
plot(likert::likert(dataLikert[, c(1:(ncol(dataLikert)-1))]),
 ↪  centered=TRUE, include.histogram = FALSE)
dev.off()

# Embed the designated font(s); device with/height points match eps
 ↪  with/height times 72
embedFonts(
  file = "./output/q7/q7q3-data-likert-plot-temp.eps",
  outfile="./output/q7/q7q3-data-likert-plot.eps",
```

```
  fontpaths = "/usr/share/fonts/",
  options = "-dDEVICEWIDTHPOINTS=627 -dDEVICEHEIGHTPOINTS=453"
)

# Plot likert (with histogram) to eps file
postscript(
  file = "/output/q7/q7q3-data-likert-histogram-plot-temp.eps",
  paper = "special",
  horizontal = FALSE,
  width = 11.40,
  height = 8.24,
  family = "Linux Libertine Display G",
  fonts = c("Linux Libertine Display G")
)
par(mar=c(0,0,0,0), las=1)
plot(likert::likert(dataLikert[, c(1:(ncol(dataLikert)-1))]), centered=TRUE,include.histogram = TRUE)
dev.off()

# Embed the designated font(s); device with/height points match eps with/height times 72
embedFonts(
  file = "/output/q7/q7q3-data-likert-histogram-plot-temp.eps",
  outfile="/output/q7/q7q3-data-likert-histogram-plot.eps",
  fontpaths = "/usr/share/fonts/",
  options = "-dDEVICEWIDTHPOINTS=821 -dDEVICEHEIGHTPOINTS=594"
)

# Plot likert (grouped by Q3; deleted NA answersets)
dataLikertGrouped <- na.omit(dataLikert)
plot(likert::likert(dataLikertGrouped[, c(1:(ncol(dataLikertGrouped)-1))], grouping = dataLikertGrouped$Q3), centered=TRUE, include.histogram = TRUE)
```

Listing 42: Question 7 – Likert Statistics

Wilcoxon Signed Rank Test

```
# Test whether the median of each sub likert question is significantly greater than a hypothized median m = 3
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]], mu=3, conf.int=TRUE, conf.level=0.95, alternative = "greater"))
}

        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 72.5, p-value = 0.8445
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
```

```
 2.000008       Inf
sample estimates:
(pseudo)median
      2.999921


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 141, p-value = 0.005996
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.500042       Inf
sample estimates:
(pseudo)median
       4.00006


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 74.5, p-value = 0.3719
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 2.500068       Inf
sample estimates:
(pseudo)median
             3


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 170.5, p-value = 0.0008788
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 3.999969       Inf
sample estimates:
(pseudo)median
      4.000034


        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 52.5, p-value = 0.6806
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 1.999929       Inf
sample estimates:
(pseudo)median
      2.999921

```

```

        Wilcoxon signed rank test with continuity correction

data:  data[[i]]
V = 39, p-value = 0.8286
alternative hypothesis: true location is greater than 3
95 percent confidence interval:
 2.00001      Inf
sample estimates:
(pseudo)median
      2.999965
```

Listing 43: Question 7 – Wilcoxon Signed Rank Test

Wilcoxon Rank Sum Test

```
# Recode Q3 in order for "Yes" being treated as the main response
data$Q3 <- factor(data$Q3, levels = c("Yes", "No"))

# Test whether the location shift for the "No" group to the "Yes"
↪  group is different to 0
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]] ~ Q3, data = data, alternative =
    ↪  "two.sided"))
}

        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 59, p-value = 0.0625
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 30, p-value = 0.434
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 43, p-value = 0.7501
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 31.5, p-value = 0.5235
```

```
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 31.5, p-value = 0.6998
alternative hypothesis: true location shift is not equal to 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 31.5, p-value = 0.6946
alternative hypothesis: true location shift is not equal to 0


# Test whether the location shift for the "No" group to the "Yes"
↪  group is less than 0
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]] ~ Q3, data = data, alternative =
    ↪  "less"))
}

        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 59, p-value = 0.9749
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 30, p-value = 0.217
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 43, p-value = 0.6589
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 31.5, p-value = 0.2618
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction
```

```

data:  data[[i]] by Q3
W = 31.5, p-value = 0.3499
alternative hypothesis: true location shift is less than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 31.5, p-value = 0.3473
alternative hypothesis: true location shift is less than 0


# Test whether the location shift for the "No" group to the "Yes" group is greater than 0
for(i in 1:(ncol(data)-1)) {
    print(wilcox.test(data[[i]] ~ Q3, data = data, alternative = "greater"))
}

        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 59, p-value = 0.03125
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 30, p-value = 0.8091
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 43, p-value = 0.3751
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 31.5, p-value = 0.767
alternative hypothesis: true location shift is greater than 0


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 31.5, p-value = 0.6851
alternative hypothesis: true location shift is greater than 0
```

```


        Wilcoxon rank sum test with continuity correction

data:  data[[i]] by Q3
W = 31.5, p-value = 0.6882
alternative hypothesis: true location shift is greater than 0
```

Listing 44: Question 7 – Wilcoxon Rank Sum Test