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Students' experiences of learning analytics in academic advising for supporting self-regulated learning

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Opiskelijoiden kokemuksia oppimisanalytiikan käytöstä akateemisessa ohjauksessa itsesäätöisen oppimisen tukemiseksi (Hanna Hooli)
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Tämä laadullinen pro gradu – tutkielma sijoittui oppimisanalytiikan ja itsesäätöisen oppimisen leikkauspisteeseen, jossa akateeminen ohjaus toimi kontekstina. Itsesäätöisen oppimisen tarkastelu rajautui käyttäytymisen säätelyyn ja tarkemmin kolmeen resurssienhallintastrategiaan: ajanhallintaan, ponnistelujen säätelyyn ja avun hakemiseen. Oppimisanalytiikan teemasta tarkastelu rajautui AnalytiikkaÄly-hankkeessa kehitettyihin omaopettajaohjauksessa käytettäviin visualisointeihin.

Vaikka opiskelijoiden mukaan ottaminen oppimisanalytiikan sovellusten kehittämisprosesseihin on tiedostettu olevan tärkeää, tällä hetkellä on olemassa vain muutamia tutkimuksia aiheeseen liittyen. Tämän työn päätavoitteena on paikata tätä aiempien tutkimusten puutetta tarjoamalla syvempää ymmärrystä siitä, miten itsesäätöistä oppimista voidaan tukea oppimisanalytiikan avulla opiskelijoiden itsensä mukaan.

Tarkemmin olin kiinnostunut löytämään vastauksia kolmeen tutkimuskysymykseen liittyen opiskelijoiden omiin haasteisiin ja tuentarpeisiin resurssienhallintastrategioista ja opintojen etenemisestä, heidän kokemuksiinsa kehitteillä olevista visualisoinneista sekä opiskelijoiden toiveista ja odotuksista visualisointien jatkokehittämiselle. Tutkittavat koostuivat kymmenestä Oulun yliopiston opiskelijasta, jotka osallistuivat AnalytiikkaÄly-hankkeen pilottitutkimukseen lukuvuonna 2019–2020. Aineistonkeruu tapahtui puolistrukturoitujen haastattelujen kautta hyödyntäen stimulated recall-metodia ja aineisto analysoitiin laadullisella teoriaohjaavalla sisällönanalyysilla, jossa haastattelujen litteroinnit toimivat tutkimusmateriaalina.

Tutkimustulokset osoittivat tähän opinnäytetyöhön valikoituneiden tutkittavien olevan hyvin pärjääviä ja yleisesti omaavan vain vähäisiä haasteita ja tuentarpeita. Opiskelijoilla oli myös erilaisia mieltymyksiä kehitteillä olevista visualisoinneista ja niiden käytöstä ohjauksessa, mikä näyttäytyi eriävinä kokemuksina. Yleisesti opiskelijat kokivat kuvaajien onnistuvan visualisoimaan haasteita ja tuen tarpeita, jonka takia ne koettiin hyödyllisiksi erityisesti enemmän haasteita omaaville opiskelijoille. Opiskelijat myös odottivat oppimisanalytiikalta erilaisia ja toisinaan jopa vastakkaisia ominaisuuksia. Tästä syystä kontrollin antaminen opiskelijoille voisi olla mielekästä, jotta voitaisiin kehittää yksilöllisesti muokattavissa olevia ja siten merkitykselliseksi koettavia oppimisanalytiikan sovelluksia. Jotta itsesäätöistä oppimista voidaan tukea tehokkaasti, tulisi myös keskittyä tarjoamaan palautetta kaikkiin sen vaiheisiin liittyen, sillä tällä hetkellä opiskelijoiden kokemusten mukaan tulevien opintojen suunnittelu ei tule tarpeeksi tuetuksi.

Avainsanat: oppimisanalytiikka, itsesäätöinen oppiminen, resurssienhallintastrategiat, akateeminen ohjaus

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This qualitative thesis was located at the intersection between learning analytics and self-regulated learning where academic advising worked as a context. The examination was limited to self-regulation of behavior and further to three resource management strategies: time management, effort regulation and help seeking. Also, the examination of learning analytics was limited to visualizations developed in a research project called AnalyticsAI.

Even though the importance of involving students’ perspectives to the development processes of learning analytics applications is well acknowledged, there are currently only few studies regarding it. The main goal of this thesis was to contribute by addressing this gap in previous research by providing insights how self-regulated learning can be supported via learning analytics according to students themselves.

More precisely I was interested in finding answers to three research questions regarding students’ own challenges and needs for support concerning resource management strategies and progress in studies, students’ experiences of the visualizations under development and students’ expectations for their further development. Participants were ten students from the University of Oulu who attended the pilot study conducted in AnalyticsAI in the academic year 2019-2020. The data of this thesis was collected through semi-structured interviews with stimulated recall –method, and was analyzed with qualitative theory directed content analysis in which transcriptions of interviews worked as research material.

The results indicated that students in this study were well-achieving and reported only minor challenges and needs for support which generally had not affected their progress in studies. Students also had different preferences regarding the current visualizations and their use in advising context which appeared as mixed experiences. Generally students experienced that visualizations make needs for support more visible and therefore they were perceived to be especially useful for students with more challenges. Students also expected different, and sometimes even controversial, features from learning analytics. Therefore, giving students control over the choice of functionalities in learning analytics would be reasonable to consider in order to develop customizable and individually meaningful learning analytics. Also, in order to support self-regulated learning, it should be made sure that learning analytics provides feedback from all phases of self-regulated learning, since students experienced that the visualizations failed to provide support for planning future studies.

Keywords: learning analytics, self-regulated learning, resource management strategies, academic advising

Contents

Introduction

In this qualitative thesis, I am interested in how learning analytics can support students' self-regulated learning and progression of studies in the context of academic advising. Majority of the previous learning analytics research is focused on course-level (Verbert, Goevaerts, Duval et al., 2014) and much less is studied on how learning analytics can be utilized in the context of academic advising and especially during advising meeting and interaction between adviser and student (Charleer, Moere, Klerkx et al., 2018). There are still few similar attempts to develop dashboards for academic advising, for example LISSA (Charleer et al., 2018) and LA-DA (Gutiérrez, Seipp, Ochoa et al., 2018), which appear to provide promising results. The focus of this thesis is on how learning analytics can support interaction in academic advising and especially how presented visualizations can support students to recognize and express their challenges and needs for support concerning their studies and self-regulated learning.

According to Matcha, Gašević, Uzir and colleagues (2019) learning analytic systems should include user-centeredness to create functionalities through which learning is effectively supported. Still, currently there is a lack of research papers regarding learner involvement in the development processes of learning analytics (Buckinham Shum, Ferguson, Martinez-Maldonado, 2019). If students were viewed as co-developers, it would enable examining what students themselves think will be useful and support their learning instead of just having assumptions of it (West, Luzeckyj, Toohey et al., 2020). However, to date, there is only little research concerning students' expectations for learning analytics.

The context of my thesis is in pilot study conducted in AnalyticsAI–project where students are involved in the development process. I have chosen to examine experiences of the learning analytics visualizations under development from student's perspective, and also examine their expectations for future in order to gain insights how self-regulated learning can be supported in academic advising according to students themselves. There is also a strong need for connecting learning analytics to the existing research of learning (Gašević, Dawson & Siemens, 2015) and especially connecting it with the context of academic advising (Charleer et al., 2018). These all examined together would provide meaningful information that current learning analytics research is lacking of, and the aim of this thesis is to contribute by addressing this gap in previous research.

The interest of this thesis is in self-regulated learning, and therefore learning analytics is connected to the work of two well-known models in the field of self-regulated learning: one proposed by Pintrich and the other proposed by Winne and Hadwin. Because self-regulated learning as a phenomenon is wide and diverse, I have limited the examination to resource management strategies and more specifically to time management, effort regulation and help seeking, which all are sections of the well-known and used Motivated Learning Strategies – Questionnaire presented by Pintrich and colleagues (1991). These resource management strategies belong to the self-regulation of behavior (Pintrich, 2000), and therefore researching them together with learning analytics and the context of academic advising, can provide interesting viewpoints concerning the potential ways to support students' learning behavior.

The focus of this thesis is at the intersection between learning analytics and self-regulated learning where academic advising works as a context, but the main goal is to provide insights how self-regulated learning can be supported via learning analytics according to students themselves. Further, the goal is to produce findings that support future development of learning analytics and its use in higher education institutions in a way that supports self-regulated learning from students' perspective.

Firstly in this paper, I will present theoretical background of this thesis including two major themes: learning analytics and self-regulated learning, and finally how they can be connected together. After that I will present the aim and precise research questions of this thesis, and then I will continue to presenting its methodology more in detail. I will start that by introducing the AnalyticsAI-project and visualizations under development because they work as a context of this research. After that I will introduce participants, which in this case refers to ten university students. Also, I will describe semi-structured interview with stimulated recall as data collection method and qualitative content analysis as analyzing method. After these I will present the results of the current study and finally conclusions, critical evaluations and ideas for future research.

2. Theoretical Background

Theoretical background of this thesis consists of two major themes: learning analytics and self-regulated learning. In addition, because this thesis is conducted within the pilot study conducted in AnalyticsAI that is currently examining how interaction between adviser and student in academic advising could be supported via learning analytics, I considered essential to include previous research on learning analytics in academic advising to this work. Further, because the focus of this thesis is more precisely at the intersection between learning analytics and self-regulated learning, theoretical background includes also previous research regarding how self-regulated learning can be supported by learning analytics. More specifically, I will start by defining and presenting previous research on learning analytics and self-regulated learning separately, and then continuing to connect these two together by presenting previous research on how self-regulated learning can be supported by learning analytics.

2.1 Learning analytics

Learning analytics is based on the fact that when learners interact with technology, they leave different kinds of digital traces, which can be collected and finally reported back as visualizations (Gašević, Dawson & Siemens, 2015). More precisely:

> "Learning analytics refers to measurement, collection, analysis and reporting of data about learners and their digital learning contexts for the purpose to understand and optimize learning and the environments in which it occurs" (Siemens, 2013, 1382).

According to Ferguson (2012), learning analytics can be beneficial for three interest groups: teachers and learners, educational institutions and governments which all have different requirements for learning analytics. Buckingham-Shum (2012) groups these levels as micro-, meso- and macroanalytic layers: macroanalytic layer operates in cross-institutional level, while mesoanalytic layer refers to institutional level, and finally microlevel analytics support the individual learners and their learning processes. In this work, the focus is on microanalytic layer and learners' perspective which in this case refers to university students. Learning analytics can provide learner an insight into their own learning processes and therefore provide recommendations for improvements, enable identifying learners that are at risk and direct support for them (Buckingham-Shum, 2012).

Greller and Drachsler (2012) present examples of how different stakeholders can be supported by learning analytics. Students can be supported for example by visualizations of specific learning processes and supporting learner's reflection that helps them to compare their achievement to the overall performance of a course (Greller & Drachsler, 2012). In addition, learning analytics can be used as a predictable tool, which can then lead to early interventions such as prevent drop-outs (Greller & Drachsler, 2012). For students, ideal learning analytics application would provide information that they can use to improve their self-regulation of learning (Roll & Winne, 2015).

2.1.1 Developing learning analytics applications

Usability plays an important role when developing new tools and applications. Buckhimham-Shum and colleagues (2019) argue that the process of developing new technologies in authentic contexts poses challenges to its technological implementation but also to its cognitive, social, political and organizational aspects. Developing efficient interactive systems requires including perspectives of all stakeholders and adopting human-centered approach, which means that all features, functions and meanings of the system should be defined by those for whom the system is intended for (Giacomin, 2014).

Matcha and colleagues (2019) present four dimensions that should be taken into consideration when developing user-centered learning analytics: theory, design, feedback and evaluation. Firstly, systems should be based on educational theories in order to efficiently impact on learning, and for the second, also the decisions of the design, for example of what kind of information is supportive and how to present it to users, should be based on previous theories (Matcha et al., 2019). Thirdly, the feedback that systems offer should be dialogical and offer only meaningful feedback instead of all available information (Matcha et al., 2019). Finally, evaluation of the actual impacts of user-centered learning analytics should be researched (Matcha et al. 2019).

In addition, because learners can be considered as primary user group of learning analytics applications (West et al., 2020), the acceptance regarding the use of learning analytics systems should also be addressed for the reason that it draws attention to privacy principles (Ifenthaler & Schumacher, 2016). Slade and Prinsloo (2013) have presented several privacy and ethical concerns regarding learning analytics and its use in educational contexts. They for example draw attention to questions regarding student privacy, data accessibility and transparency, and present also six principles to guide how these concerns could be taken into consideration in higher education institutions (Slade & Prinsloo, 2013). They emphasize the viewpoint of students as agents who are actively interacting with learning analytic systems and whose behavior can vary over time because when not focusing on that, it poses a risk to autonomy, transparency and informed consent (Slade & Prinsloo, 2013). In addition, Slade and Prinsloo (2013) address that learning analytics cannot reach learning happening outside of the learning environments or the systems where the data collection happens. Actually, even the learning that occurs within learning analytics systems does not necessarily reach the phenomenon in each and every respect (Slade & Prinsloo, 2013).

Also West and colleagues (2020) have presented few implications to guide practice: it is suggested that because students have such a crucial role in learning analytics, it would be necessary to hear what kind of ethical considerations they have instead of just having assumptions of it. Universities should include student perspectives to better understand their concerns related to learning analytics and to make sure that applications are implemented in a way that takes students' requirements into account (West et al., 2020). In addition, the data should be collected transparently with informed consent of students, and universities should ensure that users have the possibility to participate in training regarding how to use learning analytics (West et al., 2020).

Pardo and Siemens (2014) analyzed privacy issues regarding the implementation of learning analytics systems and found four categories which all should be taken into account: transparency, student control over data, security, and accountability and assessment. For example in terms of transparency, all stakeholders – including students – should have access to information of how the data is collected, stored and processed whereas in terms of students control over data, it should be possible for them to correct the data if needed (Pardo & Siemens, 2014). Also security, involving for example anonymity of data, and accountability and assessment, are presented as important topics to address within educational institutions during implementation of learning analytics (Pardo & Siemens, 2014).

Both students and academics have expressed concerns regarding the possible effects on students' autonomy when using learning analytics (Roberts et al., 2016; Slade & Prinsloo, 2013). On the contrary of usual data collection in learning analytics systems, in the project called Learning Analytics Report Card, the aim was to support student agency by allowing students themselves to choose what data they prefer to include or exclude and how the data was processed and reported back (Knox, 2017). Still, it should be acknowledged that there will always remain some challenges with the sense of control and agency because learning analytics can never be fully out of influence of institutions and their authority (Knox, 2017). In addition, profiling students can pose a risk to self-efficacy: even though profiling students enable providing supportive interventions and may potentially lead preventing drop-outs, it could also lead to stereotyping and discrimination (Greller & Drachsler, 2012).

Developing efficient learning analytics systems, which enable to support and understand individual learning processes, are current tasks for many higher education institutions (Schumacher & Ifenthaler, 2018). Therefore it is important to take into consideration what students themselves truly expect from such systems and what kind of concerns they might have (Schumacher & Ifenthaler, 2018). In order learning analytics systems to be effective, it is also important to examine users' willingness to use such systems (Schumacher & Ifenthaler, 2018). Currently many developed learning analytics dashboards lack of information regarding how learners react to and understand visualized information (Park & Jo, 2015). Therefore in this work, the interest is also on what kind of experiences students have concerning learning analytics visualizations and how understandable they consider them.

2.1.2 Learning analytics applications

There are increasing amounts of data to analyze in learning analytics, but similarly it is important to focus on data presentation, which typically takes the form of visualization, report and/or dashboard (West et al., 2020). According to Schwendimann and colleagues (2017), dashboard can be defined:

> "- -as a single display that gathers the data and different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualizations" (Schwendimann, Rodríguez-Triana, Vozniuk et al., 2017, 37).

In higher education institutions there are already several different dashboards in use for different target groups (Verbert et al., 2014; Park & Jo, 2015; Roberts et al., 2017). Usually dashboards for students reach for visualizing information that supports awareness of personal and peer learning activities and self-reflection, which then enables for example learners to set goals and track their progress towards them (Verbert et al., 2014). Furthermore, it is presented that learning analytics can potentially lead to positive outcomes, such as improvements in engagement, connection and motivation, especially when there is peer comparisons available (Verbert et al., 2014).

The focus of developing learning analytics for students should be on what kind of information is necessary and meaningful to provide rather than providing all data that is available (Matcha et al., 2019). Learning analytics feedback should also include information from different aspects of learning processes, such as where and how student is performing and what should be done next (Matcha et al., 2019). The findings of systematic review of empirical studies on learning analytics dashboards indicate that data about individuals were the most commonly used and comparisons of group averages followed usually from that (Schwendimann et al., 2017; Matcha et al., 2019). Further, the most common way to visualize such data is through bar charts (Schwendimann et al., 2017; Matcha et al., 2019). However, even though using such simple visualizations may be easier to interpret (Schwendimann et al., 2017; Matcha et al., 2019), students may still face difficulties in the interpretations of graphs (Park & Jo, 2015).

Park and Jo (2015) review and analyze features of previously developed learning analytics dashboards presented in journals and conferences between 2005 and 2013. According to them, dashboards differ from each other depending on various features, such as for whom it is developed and what are its goals: dashboards can be developed for teachers only, for both teachers and students or for students only (Park & Jo, 2015). Dashboards developed for teachers only can provide teachers information about students learning status and enable monitoring multiple students at the same time, whereas dashboards developed for students only enable monitoring their own learning patterns and support them to make changes in learning strategies if needed and support motivating their learning (Park & Jo, 2015). If the target users are both teachers and students, dashboards can provide for example learning performance compared to the whole class and information for self-reflection purposes such as awareness of how students are doing (Park & Jo, 2015).

In addition, there are multiple visualization techniques, which are linked to the characteristics of provided information that can be descriptive or predictive in nature (Park & Jo, 2015). Visualizations can roughly be divided into knowledge based and behavior based categories, which both aim at supporting self-regulated learning (Auvinen, Hakulinen & Malmi, 2015). Knowledge based visualizations can be for example simple graphs of student's progression with or without peer comparison or more complex visualizations, whereas behavior based dashboards visualize for example time spent in different activities or the number of accessed learning resources and some provide also peer comparisons which allows monitoring differences in behavior compared to other students (Auvinen et al., 2015).

According to Park and Jo (2015), visualizations usually start with descriptive analytics, but eventually it is reasonable to add also other dimensions, such as predictions. They developed learning analytics dashboard called LAPA and they found that students' overall satisfaction with the dashboard correlates with the degree of understanding of the presented information and students' perceived changes of behavior after using the dashboard (Park & Jo, 2015). The results also indicated that the dashboard didn't manage to significantly improve students' learning achievements, but the authors argue that the low perceived usefulness might stem exactly from the descriptive nature of the dashboard: in order it to be more supportive, it should have also predictive models (Park & Jo, 2015).

According to Schwendimann and colleagues (2017), previous reviews of learning analytics dashboards have concentrated more on the technical and mechanical side of such applications, for example usability, but not so much on the actual impacts to learning. Recent literature review of learning analytics in higher education institutions indicates that based on 252 research papers, there is so far not that much evidence showing improvements in learning outcomes but the strongest evidence is, however, found from the learning and teaching support (Viberg, Hatakka, Bälter & Mavroudi, 2018). Interestingly Viberg and colleagues (2018) also noted in their literature review that the use of predictive methods in learning analytics has decreased since 2016 even though they have dominated the field of learning analytics for several years. It is also suggested that the focus of learning analytics is evolving from predictive methods, towards a more comprehensive understanding of individual learning processes and experiences (Viberg et al., 2018).

2.1.3 Students as co-developers of learning analytics applications

Recently, students have been viewed as co-developers of educational applications, which enables examining what students themselves prefer to be useful and support their learning instead of just having assumptions of it (West et al., 2020). In addition, it is important to examine students' experiences to learning analytics feedback provided to them, since there is an underlying assumption that providing such analytic information to students is sufficient enough to enhance self-regulated learning (Howell, Roberts & Mancini, 2018). One potential way to develop more effective learning analytics systems can be engaging students in the development processes.

The findings of the research done by Schumacher and Ifenthaler (2018) indicate that students expect learning analytics, for example, to support their planning and organization of learning, provide some self-assessments and recommendations, and offer personalized analyses regarding their learning activities. In order to support self-regulated learning efficiently, learning analytics systems should include features from each phase of self-regulated learning (Schumacher & Ifenthaler, 2018). In addition, one of the key features when developing and implementing learning analytic tools, is the users' willingness to use such systems (Schumacher & Ifenthaler, 2018).

Also Roberts and colleagues (2017) have examined higher education students' perceptions of learning analytics dashboards and their preferred features to be included in them, and they found five different themes regarding them. First theme is called "provide everyone with the same learning opportunities" which means that if there is additional resources provided, such as materials, they should be available for everyone, and the second theme "to compare or not to compare" refers to variation of students' preferences concerning their performance compared to peers: some wanted to include such information to dashboards and some didn't (Roberts et al., 2017). Third theme included dashboard privacy which raised some concerns related to who has access to dashboards and anonymity of comparisons to peers, whereas fourth theme "automate alerts" included the preference to get automated alerts instead of personal messages from university staff (Roberts et al., 2017). Finally the fifth theme, "make it meaningful – give me a customizable dashboard", refers to different preferences for dashboards overall and the information it more specifically provides (Roberts et al., 2017).

Customization of dashboard can also be justified because previous research has shown that messages from learning analytics systems can raise mixed feelings among students: for example even positively meant messages can lead to opposite reactions and raise negative emotions, such as experiencing stress and pressure to perform (Roberts et al., 2016). In addition, negative learning analytics feedback can raise mixed experiences: it can be experienced for example as demoralizing or discouraging (Roberts et al., 2016; Howell et al., 2018).

According to study conducted by Roberts and colleagues (2017), students preferred features that support opportunities to learn, provide comparisons to peers, are perceived as meaningful and enable having at least some control over the choice of functionalities in learning analytics dashboards. If students had some control over the choice of functionalities in learning analytics, for example if they can choose whether they want to have a certain type of visualizations and are able to customize them, it would potentially enhance self-regulated learning and academic achievement through the sense of academic control (Roberts et al., 2017). However, it is still unknown what level of academic control is enough to perceive it (Roberts et al., 2017).

Roberts and colleagues (2016) examined student attitudes towards learning analytics and big data. The findings indicate that in their study, majority of students didn’t have a clear picture of what learning analytics means, which might echo the lack of informed consent in the use of learning analytics (Roberts et al., 2016). In addition, students also acknowledged different preferences regarding performance comparisons to peers, so every student should have the possibility to decide whether they want or don’t want them at all, which then can foster student autonomy (Roberts et al., 2016). Students considered the potential to form a personalized learning experience, customize support that fit to individual needs, and the feeling of individuality, as positive outcomes of learning analytics, whereas the concerns were related to privacy and not needing to use learning analytics at all (Roberts et al., 2016). Overall, the findings of the research done by Roberts et al. (2016) emphasize the necessity to involve students in decision making in order to develop acceptable, and therefore useful and meaningful learning analytic systems. This is in line with the recommended ethical principle to include learners to development processes (Slade & Prinsloo, 2013).

Ifenthaler and Schumacher (2016) examined students’ perceptions of privacy principles in the context of learning analytics systems. A total of 330 university students participated in this exploratory study and the findings indicate that students expect learning analytics to provide many kinds of support for their learning, but at the same time they may not be willing to share all their data with the systems (Ifenthaler & Schumacher, 2016). In this study the participants for example showed willingness to share data related to generally their university studies, but not the personal data regarding their online behavior (Ifenthaler & Schumacher, 2016). In addition, students evaluate the privacy issues against the potential benefits of learning analytics system: if students consider that such system can provide them meaningful information, they are more willing to share also personal data for the system (Ifenthaler & Schumacher, 2016).

2.2 Academic advising and learning analytics

In universities, for each student there is traditionally a personal academic adviser who, for example in face-to-face meetings, supports them with the process of getting their degree (Phillips, 2013). It is known that academic advising plays a crucial role to progression of studies since lack of advising or poor advising effects negatively on the progression of studies (Ali-Ansari, El-Tantawi, AbedelSalam & AlHarbi, 2015). In addition, academic advising does have an impact on student performance: advising meeting contributed to students' study skills and self-efficacy which, in turn, were related to grade point averages (Young-Jones, Burt, Dixon & Hawthorne, 2013).

Even though academic advising is known to be important to students' progress in studies and performance (Ali-Ansari et al., 2015; Young-Jones et al; 2013), there remain still questions that need better understanding. How academic advising can support self-regulated learning especially according to its main stakeholders – students themselves? What kind of possibilities learning analytics can provide for academic advising? Majority of the previous learning analytics research concerning visualizations are focused on course-level, such as face to face learning, group work or blended learning (Verbert, et al., 2014). Much less is studied how learning analytics can be utilized in the context of academic advising and especially how it could support live interaction during advising meetings (Charleer et al., 2018). However, there are few developed dashboards for academic advising, which some of them are more descriptive (Charleer et al. 2018, Phillips, 2013) and some have also predictive dimensions (Gutiérrez et al. 2018; Lonn & Teasley, 2014).

Charleer et al. (2018) developed a learning analytics dashboard called LISSA that aims to support the interaction and communication between advisers and first-year university students via describing and visualizing grade data with peer comparisons and historical data, that are commonly available in institutions, but usually only accessed by staff. The results showed that it can support students by providing insights into their study progress and support therefore future study planning (Charleer et al., 2018). In addition, it also benefits advisers, but in different ways: inexperienced advisers used the dashboard through the entire advising meeting, whereas experienced advisers used it more as a backup when needed (Charleer et al., 2018). Overall results indicate that LISSA has the potential to trigger conversations and provide facts that support argumentation, but it can't fully replace advisers because it needs to be critically interpreted with expertise (Charleer et al., 2018).

Gutiérrez et al. (2018) have also developed a learning analytics dashboard for academic advising called LADA, which goal is to support decision-making of advisers through comparative and predictive analysis. The research was conducted in two different universities and compared the new dashboard to more traditional procedures and tools, and the results show that especially inexperienced advisers perceived the developed dashboard meaningful because it manages to support accurate decision-making in same amount of time compared to the experts, and for experts LADA made possible to evaluate significantly greater number of scenarios, particularly for difficult cases (Gutiérrez et al., 2018). Especially the visualization of student data compared to peers seems to play an important role for academic advising support, but further development of the transparency of dashboard is, however, needed (Gutiérrez et al., 2018).

There is an example of dashboard that supports timely interventions called Student Explorer, which is a learning analytics tool for academic advising that aims to support not yet graduated students by categorizing their ongoing academic performance and effort by using data from learning management systems and predictions (Lonn & Teasley, 2014). It is presented to support advisers to identify students with challenges and who might be falling behind, and support triggering conversations with students regarding their performance and effort (Lonn & Teasley, 2014). Interestingly, the preliminary findings also indicate increasing in grade point averages (Lonn & Teasley, 2014).

2.3 Self-regulated learning

In addition to learning analytics, also self-regulated learning (SRL) serves an interesting viewpoint because its impacts on learning are widely accepted (Roll & Winne, 2015). Also, because differences in self-regulated learning are known to have an effect on students' learning and performance (Zimmerman, 2002; Barnad-Brak et al., 2010), it is reasonable to research how it can be supported more efficiently (Matcha et al., 2019). Self-regulated learning as a topic is so wide that this work cannot grasp the phenomenon with its whole entity. Therefore the examination is limited to those themes and aspects that are central to this work, and the intention is not to provide all-inclusive overview of the phenomenon of self-regulated learning. However, acknowledging some basic assumptions underlying self-regulated learning, are necessary in order to understand the phenomenon.

Firstly, there are several theoretical models that have been developed in the area of self-regulated learning (Pintrich, 2000). Despite the number of different theories and models, there are still some assumptions that are similar to them and the way they describe self-regulated learning (Pintrich, 2000; Schunk, 2005). All of the theories view learner as an active processor of information rather than passive recipient, they all agree that learners can truly monitor and regulate their learning as well as their cognitions and motivation to attain learning goals they have set, and finally they all highlight that self-regulated learning as a phenomenon is personal and context-bounded (Pintrich, 2000). Given these assumptions, self-regulated learning can be defined as an active and constructive process of individuals through which they plan and set goals, monitor, regulate and control their cognition, motivation and behavior in order to achieve the set goals (Pintrich, 2000; Schunk, 2005).

Sociocognitive view of self-regulated learning suggests that self-regulated learning varies not only between individuals but also within individuals (Duncan & McKeachie, 2005; Credé & Phillips, 2011). Supporting self-regulated learning is challenging because contextual, personal and situational features and their interactions have all strong affect on it (Pintrich, 2000). Still, it is relevant to consider how self-regulated learning can be supported because differences in student performance are mainly due to the different self-regulated learning capabilities (Zimmerman, 2002). In order to do so, I will firstly introduce how measuring self-regulated learning is linked to the conceptualizations of the phenomenon, and then I will present the work done by Pintrich and Winne and Hadwin. After that, I will discuss resource management strategies more in detail since they are primary focus of this thesis, and finally how self-regulated learning can be supported by learning analytics.

2.3.1 Conceptualizing and measuring self-regulated learning

In the history of measuring self-regulated learning, there are distinguished three different waves which follow the changes in the conceptualization of the phenomenon (Panadero, Klug & Järvelä, 2016). During the first wave, self-regulated learning was conceptualized in a more static way via traits and the used measurements were students' own self-reports such as questionnaires, surveys and interviews, so MSLQ and LASSI work as examples of that wave (Panadero et al., 2016). The second wave emphasized online measurements that focus on student's activity during learning tasks and it emerged because the conceptualization of self-regulated learning shifted towards process-based perspective in which self-regulated learning could be viewed as an aptitude or as an event, and therefore aforementioned MSLQ and LASSI were specified as aptitude measurements (Panadero et al., 2016).

Panadero and colleagues (2016) also suggest that currently there is a third wave going on that combines measuring the progress of individual self-regulated learning and enhancing it at the same time: for example learning diary can be viewed at the same time as a measurement tool and as an intervention to the student. In the last decade there have also been conducted studies that measure and promote student's self-regulated learning via technologies, and it is suggested that through that kind of measurement tools, students can become even more aware of their actions, and can possibly react to them by doing some changes if needed (Panadero, 2017). That is interesting also from the perspective of learning analytics and its possibilities to support self-regulated learning. However, Panadero et al (2016) highlight that the changes of the waves do not mean that the earlier measurements were replaced, but it rather means that the perspective of measuring self-regulated learning has moved from static trait-based conceptualizations to more process-oriented and contextualized features. For example self-reports are still frequently used, but now they are viewed and used more in contextualized measures or in combination with other measurements (Panadero et al., 2016).

As noted earlier, self-regulated learning can be viewed and researched as an aptitude or as an event (Winne & Perry, 2000). The most common ways to measure self-regulated learning as an aptitude is via self-report questionnaires, such as Learning and Study Strategies Inventory (LASSI) or Motivated Strategies for Learning (MSLQ), and structured interviews (Winne & Perry, 2000). If the structured interview is based on a think aloud protocol and the student is asked to describe SRL while engaging with a task, SRL is measured as an event, but if the student is asked to describe SRL after completing a task and the answers are based on memories, SRL is measured as an aptitude (Winne & Perry, 2000; Winne, 2010). In this work, self-regulated learning is examined and measured as an aptitude.

2.3.2 Winne and Hadwin's and Pintrich's views on self-regulated learning

Winne and Hadwin's model of self-regulated learning has been widely used in the field of technology supported learning (Panadero, 2017) and their model emphasizes the role of feedback (Butler & Winne, 1995) which is important for learning analytics, and therefore suits well for theoretical background of this thesis. Learning analytics dashboards can be viewed as a form of external feedback and the external feedback can impact on students' internal feedback when they evaluate their learning and goals for performance (Matcha et al., 2019). However, it does not immediately have an effect for the future if student's own goals for the task were not achieved (Butler & Winne, 1995).

The model emphazises also metacognitive perspective that views learners as active individuals who are able to manage their own learning through monitoring and metacognitive strategies (Winne & Hadwin, 1998). Metacognitive monitoring is therefore presented to be one of the key elements when self-regulating learning (Butler & Winne, 1995). However, it should also be noted that metacognition is not a distinct phase of self-regulated learning, but rather it happens through phases of monitoring and control (Matcha et al., 2019; Winne & Perry, 2000). According to Winne and Hadwin (1998), self-regulation takes place in four loosely sequenced phases and within those phases, students as agents are self-regulating their learning constantly (Greene & Azevedo, 2007; Winne & Perry, 2000). The model also emphasizes that within phases there are five components running constantly: conditions, operations, products, evaluations and standards, which can be formed as COPES-model presented more in detail elsewhere (Winne & Perry, 2000; Greene & Azevedo, 2007).

Pintrich (2000) argues that self-regulatory activities work as mediators between learners and their environments and self-regulation influences learners' achievements. Theoretical model of self-regulated learning presented by Pintrich involves two perspectives: phases of self-regulation and within each phase four possible areas of self-regulation, which are cognition, motivation, behavior and context (Schunk, 2005). The examination of this work is limited to the area of behavior for the reason that resource management strategies, that are central to this work, are involved in it. Self-regulation of behavior is defined as individuals' ability and attempts to control their overt behavior (Pintrich, 2000). According to Pintrich (2000), regulation takes place in four phases, but it is notable that even though the phases are time-ordered, there may also be situations when learner does not engage in all of the phases or areas of self-regulated learning (Schunk, 2005; Pintrich, 2000).

Forethought phase involves planning and activation, which for self-regulation of behavior means time and effort planning including schedule creations and considerations of how much time different activities take, as well as decision of the methods that will be used to evaluate the progress (Schunk, 2005; Pintrich, 2000). The next phase is monitoring of actions and their outcomes, which for behavior regulation include time and effort management, whereas the third phase includes controlling self-regulation based on monitoring the fit between goals and actions: behavior control involves general persevering even if the task is uninteresting or challenging, and seeking support outside if needed (Schunk, 2005; Pintrich, 2000). The fourth and also last phase is called reaction and reflection which includes self-evaluations regarding performance (Schunk, 2005; Pintrich, 2000). However, there is no behavioral reflection in that sense because reflection is more of a cognitive process, but the cognitions that individuals have regarding their behavior can be included in this, which means that behavior reflection involves cognitions of one's behavior, for example assessing if time have been used efficiently (Schunk, 2005; Pintrich, 2000).

The measurement tool which Pintrich developed with the colleagues, called Motivated Strategies for Learning Questionnaire (MSLQ), worked as a base for Pintrich's model of self-regulated learning (Panadero, 2017), and the validity and reliability of MSLQ is considered to be relatively good (Pintrich, Smith, Garcia et al., 1993; Credé & Phillips, 2011; Duncan &McKeachie, 2005). In addition, it is reviewed that MSLQ is the most used instrument when measuring self-regulated learning (Roth, Ogrin & Schmitz, 2016).

2.3.3 Resource management strategies

Resource management strategies refer to strategies individuals have concerning other resources than cognition and in this work, the focus is on time management, effort regulation and help seeking, which all are items from MSLQ (Pintrich, Smith, Garcia et al., 1991). Time management contains planning, scheduling and managing own study time, such as setting realistic goals, using the time effectively and setting aside blocks of time to study (Pintrich et al., 1991). According to Pintrich and colleagues (1991) they all can also be viewed in different time frames, such as weekly and monthly planning and scheduling. Effort regulation contains controlling effort and attention in uninterested or challenging tasks or when there are distractions, whereas help seeking refers individual's ability to control the support of others, such as peers and instructors, and the ability to identify own needs for support and where to seek assistance (Pintrich et al. 1991).

Students have differences regarding their self-regulated learning skills and strategies (Greene & Azevedo, 2007) and there are few studies that have attempted to distinguish different strategy profiles in self-regulated learning (Barnard-Branard-Brak, Lan & Paton, 2010; Ning & Downing 2015; Abar & Loken, 2010). Based on Online Self-Regulated Questionnaire (OSLQ) - that among other things included questions of help-seeking and time management -

Barnard-Brak et al. (2010) found five distinct profiles of how individuals are and are not self-regulated. The research was replicated across two study samples in online learning environment, and the results reveal significant differences in academic achievement depending on the profiles (Barnard-Brak et al., 2010). Also Abar and Loken (2010) examined self-regulated learning with a sample of 205 high-school students by using Motivated Strategies for Learning –Questionnaire (MSLQ), which included questions of time management and effort regulation, and the Patterns of Adaptive Learning Scales (PALS), and found a total of three profiles: high, average and low self-regulated learning profile (Abar & Loken, 2010).

Previous research indicates mixed results regarding resource management strategies and their effect on academic outcomes. It is, for example, suggested that self-efficacy and effort regulation can predict academic achievement: students who tend to persist in uninteresting or challenging tasks, are more likely to perform well, be more self-motivated and less likely to seek help outside (Komarraju & Nadler, 2013). In addition, meta-analysis done by Broadpent and Poon (2015) indicate that in higher education context time management and effort regulation were significantly but only weakly correlated to academic achievement. However, research conducted by Kumrow (2007) revealed that within a hybrid learning environment for nursing education, there weren't any significant correlations between course grades and self-regulatory strategies, such as time management, effort regulation, study environment and peer learning. The only self-regulatory learning strategy that showed a significant correlation was help seeking (Kumrow, 2007).

2.4 Supporting self-regulated learning by learning analytics

Learning analytics has the potential to provide interesting opportunities for analyzing and supporting self-regulated learning and agency. For students, ideal learning analytics tool would provide information that they can use to better self-regulate their learning, for example information regarding options within the phases of self-regulated learning (Roll & Winne, 2015). There are, however, both challenges and possibilities, when trying to support self-regulated learning by learning analytics, as Roll and Winne (2015) state:

> "Overall, the intersect of learning analytics and SRL offers a grand challenge. Grand in its magnitude; grand in its potential impact; and grand in that opportunities for meaningful progress are within reach" (Roll & Winne, 2015, 11).

Supporting self-regulated learning is not a simple task because it varies between and within individuals and is affected by multiple contextual, personal and situational factors as well as interactions between them (Duncan & McKeachie, 2005; Credé & Phillips, 2011). Because there are so many challenges, it is important to continue trying to find ways how to support self-regulated learning more efficiently. External feedback provided by learning analytics has the opportunity to affect students' internal feedback of assessments between their learning and goals, and therefore enhance the accuracy of such evaluations (Matcha et al., 2019). There is, however, a need to better understand what kind of feedback is perceived useful and meaningful for supporting self-regulated learning according to students themselves, which is under research in this thesis.

Research to date indicates that there is some support for the positive impact of the use of dashboards when supporting self-regulated learning and motivation. One example of dashboards that aim to support timely interventions such as immediate feedback instead of giving feedback when courses have already completed, is called Course Signals at Purdue University, which aims at predicting student success by using information from student's interactions with learning management systems, past academic history and demographic characteristics (Arnold & Pistilli, 2012). Students got feedback about their progression of studies in color codes via an email sent from faculty member, and the results indicate that dashboard has an impact on student's retention and grades: students, who could use the dashboard earlier and in more courses, were more likely to continue their studies and perform better (Arnold & Pistilli, 2012).

Auvinen, Hakulinen and Malmi (2015) provided students heatmap visualizations that made possible for students to monitor their own behavior in comparison to the behavior of the students from past courses, and based on that offered prediction of student's success if his/hers behavior stays the same during the course. They aimed at researching if such visualizations increase students' awareness of their own behavior and therefore improve their study practices (Auvinen et al., 2015). Results indicate positive impacts to students study practices as well as performance, but the same type of visualized information is not suitable for all students due to individual differences: the ones, who were the most interested in heatmap visualizations, were already high-performing students (Auvinen et al., 2015). The authors suggest that visualizations cannot create a desire to self-regulate if student herself/himself has no interest in doing so but rather visualizations can potentially support the ones who already are at some level regulating their learning (Auvinen et al., 2015).

It is also presented that learning analytics dashboards can support learning if they include feedback from its underlying self-regulatory processes (Zimmerman, 1990; Sedrakyan et al., 2018; Matcha et al., 2019). It is interesting that many of already existing learning analytics dashboards, however, focus on providing performance visualizations by outcome feedback, such as how a student is performing, instead on process-oriented feedback that triggers questions of how to perform better (Sedrakyan et al., 2018). Usually feedback consists of information about levels of student engagement and performance and can also include peer comparisons regarding performance (Howell et al., 2018) which at a general level aim at increasing students' self-awareness, self-reflection, motivation and finally enhance learning experiences (Schwendimann et al., 2017; Park & Jo, 2015; Verbert et al., 2014).

Providing peer comparisons, such as group averages, are commonly used in many learning analytics dashboards (Matcha, 2019), but they may not be suitable for everyone (Sedrakyan et al., 2018). Also, Sedrakyan and colleagues (2018) point out that peer comparisons can support self-regulated learning for those students, who do not have adequate motivation for setting goals and for those, who are performance or avoidance oriented learners (Sedrakyan et al., 2018).

Sedrakyan and colleagues (2018) have recently presented how learning analytics dashboards can provide cognitive and behavioral feedback through learner profiles based on phases of self-regulated learning. Cognitive feedback aims at supporting self-regulated learning at a task-level and improving learning outcomes, whereas behavioral feedback aims at changes in behavior by offering information indicating needs for behavioral change and improving awareness of learning progress (Sedrakyan et al., 2018). Further, in dashboards, the role of behavioral feedback is to provide information if learner is "on track" (Sedrakyan et al., 2018).

Planning profiles can provide guidelines to learners and inform teachers of the fit between goals and action plans, and they can be useful when considering the overall preparedness, preferences and difficulties of students (Sedrakyan et al., 2018). Because monitoring should enable student to adjust goals, plans and strategies for learning when needed, monitoring profiles can provide information concerning study progress compared to an action plan and self set goals, whereas adaptation profiles can provide insights of the level of effort and possible needs for adjustments, such as how they tend to perform with challenges and how much time they tend to spend (Sedrakyan et al., 2018). However, in order to make firm conclusions, further research about evaluating actual impacts of the model is still needed.

3. Aim and research questions

The focus of this thesis is at the intersection between learning analytics and self-regulated learning where academic advising works as a context. It is based on the view that students are co-developers of educational applications, and therefore the focus is on examining what students themselves think will be useful and support their learning instead of having assumptions of it (West et al., 2020). Currently there is lack of research papers reporting students' involvement in learning analytics development processes (Buckinham Shum et al., 2019) and broader only few reported studies of students' expectations of learning analytics (Schumacher & Ifenthaler, 2018 and 2016; Roberts et al., 2016; Roberts et al., 2017).

The aim of this qualitative thesis is to contribute by addressing this gap in previous research by providing insights how self-regulated learning can be supported via learning analytics according to students themselves. Further, the aim is to produce findings concerning students' experiences of the current visualizations developed in AnalyticsAI and students' expectations for their further development. In a broader sense, this work also aims at providing findings that support future development of learning analytics and its use in higher education institutions in a way that supports self-regulated learning in students' perspective.

The selection of research questions has been guided by my interest in learning analytics and self-regulated learning as separate phenomena and how they can be connected together. In the field of self-regulated learning, I have limited the examination to resource management strategies that are based on MSLQ-questionnaire presented by Pintrich and colleagues (1991). In the field of learning analytics, the examination is limited to visualizations in academic advising context that are currently under development in the AnalyticsAI-project.

More specifically this thesis focuses on finding answers to following three research questions:

1. What kind of challenges and needs for support students have concerning resource management strategies and progression of studies?
2. What kind of experiences students have about the learning analytics visualizations in academic advising for recognizing their own challenges and needs for support?
3. What kind of features students expect from learning analytics visualizations in order them to benefit their self regulated learning and progression of studies?

4. Methodology

Next I am going to present more in detail how this research is conducted: participants, chosen data collection and analyzing methods and procedures. The aim is to describe methodology as detailed as possible in order to increase transparency and evaluation of this research. Because the context of this research is in AnalyticsAI-project, I will start with introducing it and the examples of visualizations under development and research. After that I will continue to presenting participants, interviews as data collection method and qualitative content analysis as analyzing method.

4.1 Context: AnalyticsAI-project

AnalyticsAI is a two-year project, started in August 2018 and lasting until December 2020, which aims to research, pilot and develop new ways for supporting fluent study paths with learning analytics in the context of higher education (AnalyticsAI, 2019). The focus is on developing learning analytics tools that can support different stakeholders in university: students, teachers and guidance as well as educational leadership and university governance (AnalyticsAI, 2019). The project is funded by Finnish Ministry of Education and Culture and it involves seven different universities in Finland: University of Oulu, Aalto University, University of Eastern Finland, University of Lapland, LUT University, Tampere University and University of Turku (AnalyticsAI, 2019). The University of Oulu coordinates the whole project and utilizes its research of educational psychology for developing fluent studying, advising and management practices in higher education (AnalyticsAI, 2019).

During academic year 2019-2020 a pilot study has been conducted for learning analytics visualizations that are developed for teacher tutors who are academic advisers for students in an institution. The visualizations aim at visualizing students' progression of studies and are currently used in academic advising session. Only teacher tutors had access to these visualizations and with students, they were viewed only during advising meeting. Therefore students didn't have independent access to these visualizations. In addition, teacher tutors had the possibility to decide whether they use all of these visualizations or if they use only few or none of them in advising meeting.

The context of this thesis is dated on this phase of pilot study, and the focus is on using the visualizations during academic advising meeting because currently it is the only chance for participated students to actually access the visualizations. I am interested in how students experience the given visualizations and were they perceived to support students' self-regulated learning and progression of studies. More specifically, I am interested if the given visualizations can support students to recognize and express their challenges and needs for support concerning their studies and resource management strategies. Furthermore, the focus is on what kind of features students expect from learning analytics in order it to support their self-regulated learning and progression of studies. Next I am going to introduce examples of the visualizations under development.

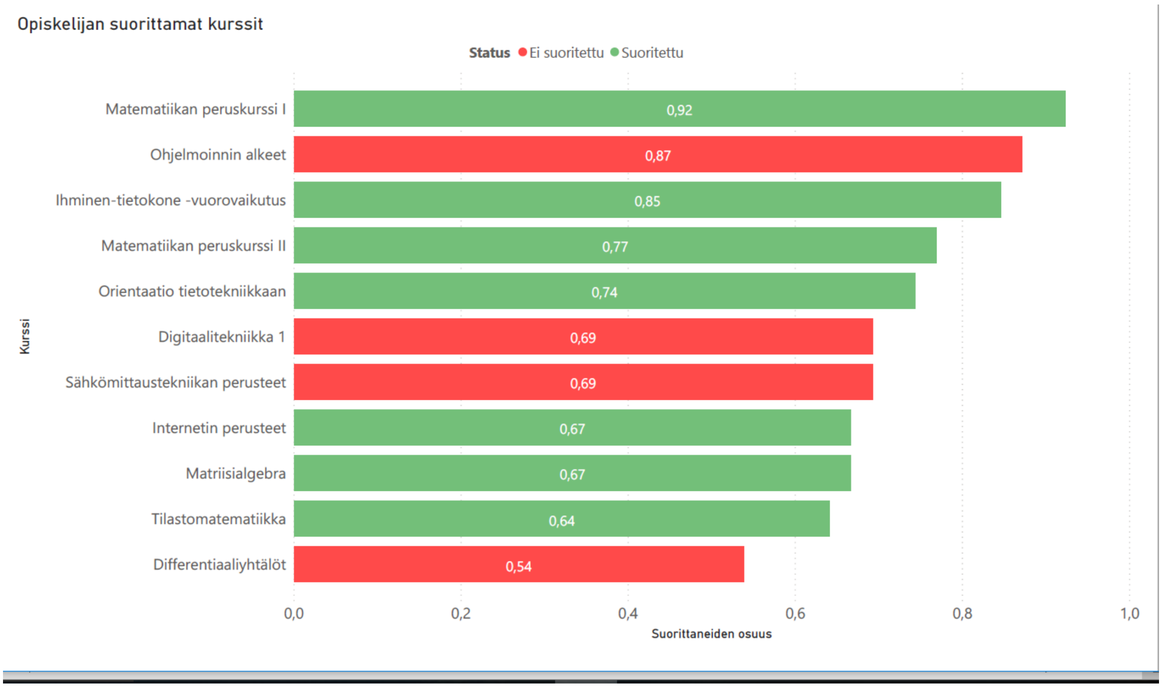


Figure 1. Bar chart of student's completed and non-completed courses

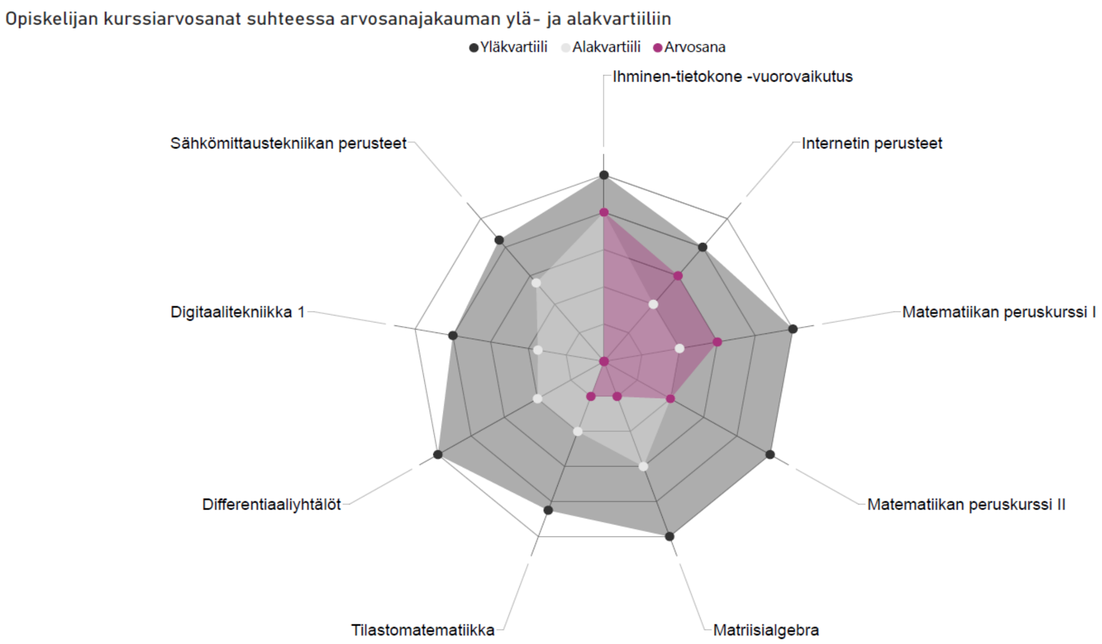


Figure 2. Radar chart of student's course grades compared to inter-quartile range of peers' course grades

Figure 1 illustrates students completed and non-completed courses that student has chosen to take to personal study plan within an ongoing academic year. The vertical axis of bar chart illustrates student's planned courses and the horizontal axis, in turn, illustrates the percentage of students who registered to the same course in a same academic year and who have completed the course. Bars are also color-coded: green color indicates passed completed courses and red color indicates non-completed courses. Red color may stem from either failed courses or those courses that student have planned to take, but is not yet completed. The number inside bars indicates percentage of students who registered to the same course in a same academic year and who have completed the course, which is also illustrated via the length of each bar.

Figure 2 illustrates student's course grades from courses, that he/she has chosen to take to personal study plan within an ongoing academic year, compared to inter-quartile range of peer's course grades. Student's completed courses work as variables and the scale indicates course grades ranging from zero to five. In the centre is zero, which means failed course, and from there the scale moves towards greater numbers so that the grade five stands outermost. The actual data points indicate student's own course grades which are then connected together with a line to create a polygon. The radar chart can be viewed with or without the comparison information, and is also color-coded: the pink polygon illustrates student's own course grades and the darker grey illustrates comparative information. Comparative polygon includes information of peers' course grades from the same class with the exception of the highest and lowest achieved 25%, so there remains only inter-quartile range of peers' course grades. The white data point indicates lower quartile and the black data point upper quartile, and between them remains 50% of the distribution of peers' course grades.

4.2 Participants

The participants were ten second- and third-year students from the Faculty of Information Technology and Electrical Engineering (ITEE) and the Faculty of Education, who participated in pilot study conducted in AnalyticsAI-project at the University of Oulu. Further, the sample of this thesis consists of students who attended academic advising meeting in autumn and winter 2019-2020 and who attended semi-structured interview after the advising meeting. The final sample size consisted of a total of ten student interviews: eight students from Faculty of Education and two students from the Faculty of ITEE. In the AnalyticsAI-project, the students were recruited via teacher tutors who sent their students an e-mail concerning the pilot study. Then the volunteered students participated in a pilot study and ten of them also volunteered to be interviewed for this thesis.

Because this was part of a pilot study, not all of the students were able to monitor their personal visualizations during the academic advising meeting due to technical problems. Two students from Faculty of Education didn't use the visualizations in advising meeting at all for that reason. They are still included to the participants of this thesis since they might raise interesting viewpoints, and it enables gaining information how students could experience the visualizations when seeing them for the first time. During the interview, mock-up visualizations were showed for those participants who did not use the actual visualizations during the academic advising meeting and their interview questions were modified (Appendix 1, interview protocol, version two) so that they could answer even though they didn't use visualizations in advising meeting. Mock-ups didn't include any personal data but were only examples of the visualizations.

There was also variation of which visualizations were monitored and used in academic advising meeting because some of the teacher tutors didn't want to use all of the visualizations with some students. In advising meeting teacher tutors had the possibility to control if they viewed all or only some of the visualizations. Because of all the aforementioned, there were two students who didn't use any visualizations in the advising meeting, five students who did use all of the visualizations and three students who did use all visualizations except the comparison with peers. This kind of variation between participants undoubtedly sets challenges to the evaluation of this research.

4.3 Semi-structured interviews with stimulated recall

In line with models of self-regulated learning (Pintrich, 2000; Winne & Hadwin, 1998), I adopted the view that learners are agents who are able to interact with learning analytics systems and whose behavior might vary over time. Also, research in learning analytics highlights the need to examine what kind of experiences students themselves have concerning learning analytics (Ifenthaler & Schumacher, 2018; Roberts et al., 2017; Matcha et al., 2019; Buckingham-Shum et al., 2019). Based on these, I assumed that the data can be collected successfully through interviewing students themselves.

Prior research has outlined that interview knowledge is both socially constructed and actively created in the interaction between participants of the interview, and the language works as a tool for obtaining and producing the information (Kvale & Brinkman, 2015). The production of knowledge, however, continues in transcriptions, analyses and reporting the results, so the interviewer itself can be considered as an instrument for producing knowledge (Kvale & Brinkman, 2015). Also, interview knowledge is presented to be relational, conversational and contextual: knowledge produced in interview does not necessary mean that it can be applicable to other situations (Kvale & Brinkman, 2015).

The main purpose of qualitative interview is to understand the lived experiences from the perspective of subjects themselves (Kvale & Brinkman, 2015). The degree of structure, however, varies from very structured interviews to open interviews depending on the research questions and goals of researcher itself (Galletta, 2013). I ended up choosing semi-structured interview because of its flexibility and its strengths: it allows studying specific theory-driven variables while at the same time leaving space for interviewees to provide new insights and meanings to the topic (Galletta, 2013). In addition, it allows considerable reciprocity and opens possibilities to ask the interviewee to specify certain answers (Galletta, 2013). Given these, I thought that particularly semi-structured interview would fit best to the research questions of this thesis: while the questions of resource management strategies are strongly theory-driven, I wanted to make sure students' voices were heard and leave space for their experiences instead of defining too strict frames in advance.

In this work, self-regulated learning was examined as an aptitude, and therefore the questions were formed in a way that students answered them based on their memories (Winne & Perry, 2000; Winne, 2010). Kvale and Brinkman (2015) point out the role of memory in interviewing: recall process should be supported in order the interviewees' descriptions to be valid and close to the lived experience. For this reason, stimulated recall was also included to support recalling process. Stimulated recall can be grouped to introspective research methods and it is considered to suit especially examining processes of learning, interpersonal skills and decision-making (Hodgson, 2008) in research contexts of counseling, nursing and education (Lyle, 2003). It aims at stimulating thoughts or feelings examinees were having during the time of the actual event (Hodgson, 2008) usually via videotapes, but generally it is known to be flexible research tool (Lyle, 2003). In this thesis, the stimulation happens via student's personal visualizations used in academic advising meeting with the teacher tutor.

However, stimulated recall generally is not widely viewed as an useful approach: it is for example criticized that examinees may still not report the feelings and thoughts based on recall but may report how they currently are reacting (Hodgson, 2008). Also, critique addresses that there is a difference between recalling an event and reflecting the event (Hodgson, 2008). Despite of these, stimulated recall is still generally perceived to produce useful knowledge for examining people's experiences concerning specific event or interaction (Hodgson, 2008). In order to increase validity, the recall should happen as soon as possible after the actual event because the sooner it is arranged the better is recalling (Hodgson, 2008).

Before the main data collection phase, a pilot interview was conducted to test the interview protocol. Pilot interview included one student from Faculty of Education who did not have any experience or knowledge of the AnalyticsAI-project. Based on that pilot interview, some questions were reformulated and reordered. The development process of the interview protocol included also feedback from researchers working in AnalyticsAI and therefore faced multiple iteration rounds before setting to its final form. The final form is presented in Appendix 1.

The volunteered students signed a paper to make sure their participation is based on free will and informed consent. In AnalyticsAI there were multiple data collection methods such as surveys before and after advising meeting. The interview took place after the advising meeting and majority of students had also done the surveys as well before the interview. Because informed consent is an important ethical guideline in interview research (Kvale & Brinkman, 2015) I wanted to make sure students' participation was based on that, and sent an e-mail before the interview containing info letter about the AnalyticsAI-project and the interview, even though the same info letter was given also earlier.

The data of this thesis was collected between November 2019 and February 2020. The interviews aimed to describe and understand different experiences that students have about their studying, study progress, use of resource management strategies and experiences of the academic advising meeting with new visualizations, in order to gain insights into research questions of this thesis. Interviews were carried out in reserved room at the university campus, within two weeks of student's academic advising meeting. The interview durations ranged from 18 minutes to 80 minutes and were also audio-recorded for later analysis.

Interviews followed the interview protocol (appendix 1) starting with general questions of student's experiences of studies in university and the progression of studies to the use of resource management strategies. Before questions concerning experiences of the visualizations under development were presented, the interviewer presented each student's own visualizations to stimulate the recall process. Because there were two students, who did not use visualizations during academic advising meeting at all, mock-up visualizations in figure 1 and 2 were presented for them. For them, the interview questions concerning experiences of the current visualizations and expected features were also formed in a way that they could answer them accurately (appendix 1; interview protocol, version 2). The transcription of interviews was arranged by AnalyticsAI-project and it included only manifest, not latent, content of the interactions with interviewer.

The privacy of students and ethical principles were handled carefully: only researchers in AnalyticsAI could access personal data of participants and that information were used only for the purpose of research. In addition, every student had the right to draw back from research and ask for deletion of their research material at every stage of research. Audio recordings of interviews didn't include any questions of students' identity except information of studying years in current study program. I coded students as numbers after the interviews and used only those numbers after the data collection phase. Because of all this, the person who transcribed the audio recordings didn't know who were the persons involved in interviews. After this research is fully completed, I will delete all the information and transcriptions of interviews.

4.4 Qualitative content analysis

The transcriptions of ten student interviews work as a research material for qualitative content analysis of this research.

> "Qualitative content analysis is a method for systematically describing the meaning of qualitative material. It is done by classifying material as instances of the categories of a coding frame" (Schreier, 2012, 1).

Also Hsieh and Shannon (2005) define qualitative content analysis as a research method that involves subjective interpretation of contents of research material that happens via systematic classification. However, it should be noted that through qualitative content analysis, it is impossible to describe the meaning of researched phenomena in each and every perspective (Schreier, 2012). The aim of qualitative content analysis is to reduce data and therefore it is a good method when there is lots of research material that needs to be summarized (Schreier, 2012). Also, it is particularly used method for analyzing text data (Hsieh & Shannon, 2005; Elo, Kääriäinen, Kanste et al., 2014). In this thesis, there were 86 pages of transcriptions of semi-structured student interviews to be analyzed, so I considered qualitative content analysis as a suitable analyzing method for this thesis.

Hsieh and Shannon (2005) present three approaches of qualitative content analysis: conventional, directed and summative content analysis. Because resource management strategies, that are in particular interest of this thesis, are based on theory, I decided that the approach in this work is directed content analysis in which theory works as a guide for analyses (Hsieh & Shannon, 2005). According to Schreier (2012), the analysis can be conducted in a concept-driven way, data driven way or combining these. Because I wanted to leave space for students' experiences, I ended up combining concept-driven and data-driven ways, which is also presented to be the most used way (Schreier, 2012).

For the first research question I decided to proceed purely with concept-driven way and created a loose coding frame in advance just like Schreier (2012) recommended. Also Hsieh and Shannon (2005) present this as one strategy to start the analyzing process. For the second and third research question the method was first inductively group similar contents together and after that look back to theory if there were categories suitable for their analysis. In spite of these variations in analyzing processes, all of these can be classified under directed content analysis approach, in which codes can be defined before or during the data analysis (Hsieh & Shannon, 2005).

In directed content analysis, the discussion of research findings is guided by theory which then might lead to contradictory findings, expansion or further refining the existing theory (Hsieh & Shannon, 2005). It is, however, criticized that the use of directed content analysis usually fosters finding results that are in line with the directing theory, and overemphasizing theory might even lead to neglecting contextual features of researched phenomenon (Hsieh & Shannon, 2005). In addition, qualitative content analysis overall has been criticized for being too simple a method (Elo & Kyngäs, 2008). One challenge of conducting qualitative content analysis is also its flexibility: there is no simple "right" ways to do it and no specific guidelines transferrable to every situation (Elo & Kyngäs, 2008).

There are also different terms in use when evaluating qualitative content analysis: it can be evaluated with concepts of validity and reliability just like quantitative content analysis (Schreier, 2012), but there are also other terms such as trustworthiness which in turn involves credibility, dependability, conformability, transferability and authenticity (Elo et al., 2014). Credibility refers to accurate identification and descriptions of the participants of current research, whereas dependability focuses on data stability under different conditions and times (Elo et al., 2014). Conformability involves considerations of objectivity, whereas transferability means considerations if the findings can be applicable to other research settings, groups, or more generally considerations of generalizations (Elo et al., 2014). Authenticity, in turn, refers to the extent to which researcher shows the range of realities, an these all can be evaluated in every step of analysis all the way from preparation phase to reporting findings (Elo et al., 2014).

(Internal) reliability in qualitative content analysis involves consistency of the coding, which can be assessed by comparing coding across persons or across different points of time, and validity, in turn, refers to evaluations if the formed categories truly manage to represent the concepts under research (Schreier, 2012). However, neither reliability nor validity can never be completely fulfilled: the coding is valid or reliable only to a certain degree (Schreier, 2012). When evaluating the validity of data-driven coding frames, the main focus should be on face validity which means that instrument should capture what it is suppose to capture, whereas in concept-driven coding frames content validity is presented to be more useful (Schreier, 2012). Content validity involves evaluating if the coding covers all dimensions of a concept under research (Schreier, 2012) and it is presented to be necessary to report clearly how the research results were produced through analysis in order to support evaluating validity (Elo et al., 2014). Therefore I will present next the analyzing procedure more in detail.

4.4.1 Analyzing procedure

I decided to follow the analyzing procedure of qualitative content analysis described by Schreier (2012) because the guidelines presented in it were specific enough to use the analyzing method. According to Schreier (2012), the first step after formulating research questions and selecting material is to create a fitting coding frame which starts of the decision whether to begin with breaking down the data according to topic or according to source. I decided to break down the data according to topic. In addition, preparation phase includes selecting unit of analysis before the main coding (Elo & Kyngäs, 2008; Schreier, 2012) and because it is in particular interest of this thesis to examine contents from students' interview responses, I considered it reasonable to choose content as unit of analysis. Therefore references of transcriptions form units of analysis in this study.

According to Schreier (2012), the next step is to distinguish relevant and irrelevant contents in respect of research questions. In order to do that, the transcribed interview data were imported to QSR NVivo 12 plus –software. I started reading the transcriptions multiple times first to gain a sense of the whole, and then another round without highlighting, and the second and third round by highlighting contents that were relevant to research questions of this thesis. Schreier (2012) points out that if in doubt when distinguishing relevant and irrelevant data, it should be coded as relevant because excluding data that might still be relevant should be avoided and it is better to make a mistake on the safe side. After that step I created starting nodes, which in this case were research questions of this thesis, because I considered it helpful for distinguishing which relevant data were related to which research questions. I also added descriptions of what those nodes more specifically included and what was excluded.

For the first node I decided to include every answer that mentioned challenges and needs for support concerning studies and resource management strategies. I also included answers that mentioned directly a lack of challenges and needs for support concerning studies and resource management strategies because in my opinion they are also important findings of this research and are considered as relevant content to the first node. Anything that did not fit into these descriptions, were excluded.

For the second node, I decided to include all the answers that contained experiences of the visualizations and their use in advising meeting from the perspective of resource management strategies. Therefore they included both positive and negative experiences. In addition, I included experiences of their understandability and functionality, as well as what kind of lacks and flaws were detected by individual students. For the third node, every answer that contained development ideas, expected and unexpected features and policies concerning learning analytics and/or its use in university, were included. I also included those answers that mentioned if something would not benefit student itself but would probably be useful for some other students.

The next step according to Schreier (2012) is to structure coding frame and generate subcategories, which can be done in a concept-driven way, data-driven way or combining these. I decided to proceed with one research question at a time starting with the first question to the second and finally third. For the first research question, I created a loose coding frame based on theory before I started coding the content. It consisted following main categories: time management, effort regulation and help seeking, which all are items from MSLQ (Pintrich et al., 1991). However, I did not create any subcategories for them in advance. According to Schreier (2012), concept-driven coding frame can be loose so that it only consists of the main categories and the content of subcategories can be added inductively.

With the second and third research question, the approach was theory directed so that I did not create a specific coding frame in advance but rather inductively grouped similar contents together and then looked back to theory if there were suitable categories for those groupings. Therefore it combined data-driven and concept-driven strategies. I ended up creating four main categories for both second and third research question based on three earlier mentioned resource management strategies and one category that included answers containing understandability and functionality of the used visualizations or of expectations for future.

To make sure everything relevant was included, I took several coding rounds for each main category. After that, I examined more in detail what kind of contents were coded in each main category. Based on those examinations, I did groupings of similar contents similarly as described with the creation of main categories: first inductively and then looking back to theory. I utilized the descriptions of each resource management strategy mentioned in MSLQ (Pintrich et al., 1991) when creating subcategories. I also added definitions of each subcategory regarding what the subcategories include and exclude and gave examples to guide coding. According to Schreier (2012), these definitions should include at least a name, description of contents and examples. If there were contents that could be coded into several categories, I cut them into pieces and then coded those pieces into different categories, and also added decision rules to guide coding when there were overlapping contents. This was done because there is requirement of unidimensionality: each dimension should capture only one aspect of analyzed material (Schreier, 2012).

The last step, when building a coding frame, is to revise and expand the created frame and make sure it is exclusive and without mixing dimensions (Schreier, 2012). I took time to check all the material for any structural inconsistencies. Finally the coding frames for each three research question took shape of the following figures:

Figure 1. Coding frame for first research question

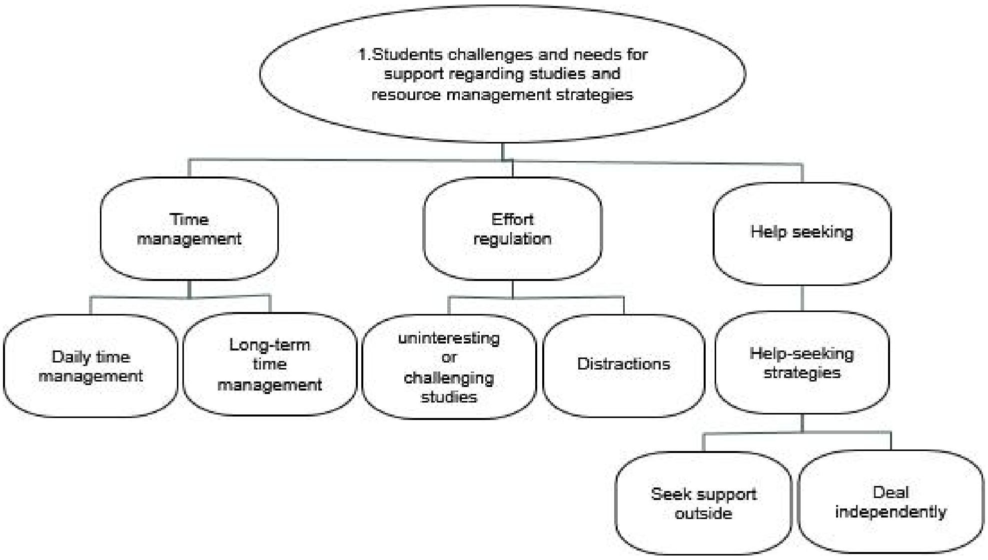


Figure 2. Coding frame for the second research question

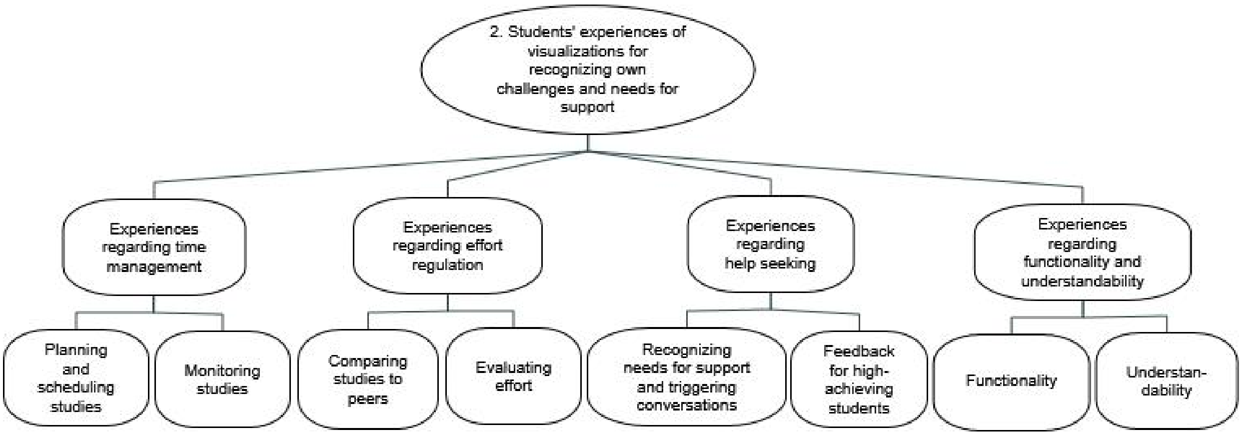
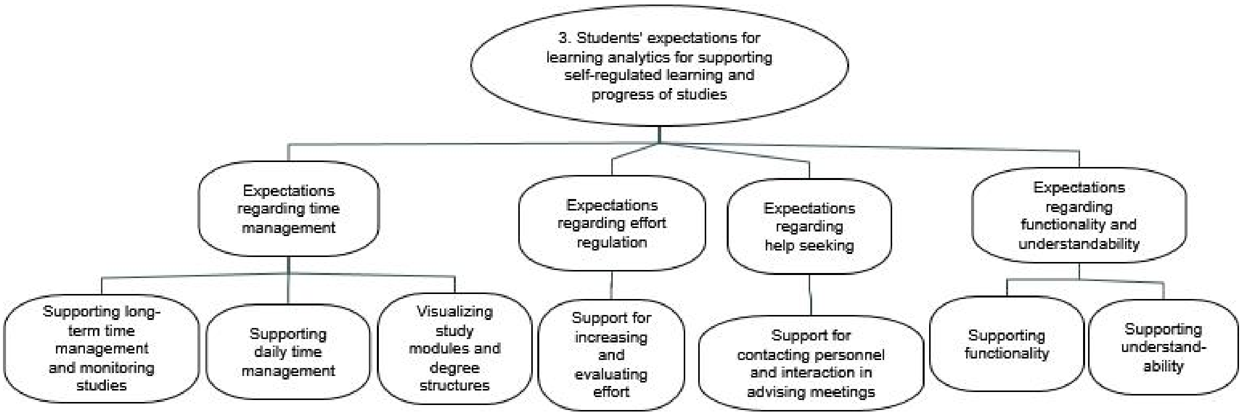


Figure 3. Coding frame for third research question



After coding all the relevant material into these categories of each research question, I started counting frequencies of the coded references in each main- and subcategory. With the first research question, I also counted amounts of students included in each main category because I thought it would provide meaningful information particularly of participants of this research. With the second research question I also divided the experiences from each subcategory into positive and negative experiences and counted frequencies of coded references in them so that I would get a clear overall view if there were more positive or negative experiences.

When the coding was fully completed, I decided to assess its inter-coder reliability by comparing the coding with other person and evaluating the percentage of agreement, which provides a summary regarding consistency of the coding (Schreier, 2012). The other coder was working in AnalyticsAI, but she had no specific knowledge of my thesis. I took randomly 10-20% of analyzing units from each main category to be coded again and gave detailed guides and descriptions of categories to the coder. I distinguished the analyzing units under each research question in advance and the coder had to code them into main categories and after that into subcategories. There were a total of 50 analyzing units with four disagreed and 46 agreed coded analyzing units, which indicated that the percentage of agreement was relatively high (92%). There were one disagreed analyzing unit regarding both the first and the second research question, and two disagreed analyzing units in the third research question. Based on that, I specified the descriptions of categories but decided not to make any changes in the coding.

After assessing the inter-coder reliability with the percentage of agreement and counting frequencies of each main- and subcategory from all research questions, I started forming tables one research question at a time for describing the main contents within each subcategory. Next I am going to describe the results of contents and their frequencies more in detail including also the formed tables.

5. Results

Next I am going to present results of qualitative content analysis based on transcriptions of ten semi-structured student interviews. The aim is to provide descriptions of contents in each main- and subcategory and also add information of proportions of those categories. Therefore I decided to use frequencies of both coded references and the amount of participants in order to describe the proportions of categories. It enables examining how common certain categories are and therefore would potentially provide meaningful information for future development of current visualizations. Results are presented one research question at a time starting with the first question and ending with the third research question. Also, in order to gain a sense of the whole, I added summary of the main results from all research questions at the end of this chapter.

5.1 Students' challenges and needs for support regarding studies and resource management strategies

In the first research question I was interested in what kind of challenges and needs for support students have concerning resource management strategies and progression of studies. Table 1 illustrates the frequencies of coded references in each main category and amounts of students who experienced to have at least some challenges with specific resource management strategies and studies.

Table 1. Students' challenges and needs for support regarding studies and resource management strategies

Challenges regarding	Students (f)	Coded references (f)
Time management	8	28
Effort regulation	9	28
Help seeking	1	2
Total	**10**	**58**

As the table 1 demonstrates, students' major challenges and needs for support were related to time management and effort regulation. However, majority of students responded that their challenges and needs for support were not so severe that they had impact on to their progression of studies. Also, the result of help seeking was radical: only one student responded to have challenges with it and especially regarding where to seek support. Further examinations of students' help seeking strategies indicate that nine students out of ten knew clearly how to proceed when facing challenges. Majority of them would try first independently and after that seek support outside for example from peers, teachers and teacher tutors.

5.1.1 Time management

Results show that eight students, with 28 coded references, expressed to have some challenges concerning time management, of whom three expressed to have only minor temporary challenges. Two students, in turn, expressed directly a lack of challenges with time management. However, despite that the majority of students reported to have at least some challenges with time management, nine students out of ten expressed directly that they do not experience the need for support concerning time management. Only one student responded that she had felt the need for such support earlier in her studies but not so much anymore.

Daily time management

Challenges can occur in different phases of self-regulation: planning, monitoring, controlling or reflecting. Challenges with daily time management included responses from seven students and 17 coded references. Even though seven students responded to have challenges with daily time management, interestingly six of them expressed that challenges had occurred in the controlling phase when there was too much to do and too little time left due to the sum of deadlines or due to starting studying at the last minute. Also, one student expressed challenges with daily time management in the controlling phase due to technical problems with internet connections or the tools that are used when doing teamwork online. Therefore in total all seven students, who responded to have challenges with daily time management, had experienced them when implementing actions.

Also, four students had experienced challenges in the planning phase, for example some expressed directly a lack of daily planning or feeling negative emotions when planning, such as:

> *"I don't use any* [plans for daily time management]. *I probably should."*

> *"Even when I don't have many courses or maybe exactly because of that, it feels stressful to plan and schedule everything."*

> *"I didn't know how to plan back then* [1st year in university] *and I didn't for example write down any assignment dates. - - There were so many courses that left uncompleted because I just didn't know how to schedule them to my daily calendar"*

In addition to challenges in planning, one student, who expressed a total lack of challenges regarding time management, still expressed that he should track his study time and see where the time goes because it would help further planning.

These results of this subcategory generally indicate that some students do have challenges with daily time management which then may appear in different phases of self-regulated learning, for example as negative emotions or as lack of scheduling skills when planning, and lead even to uncompleted courses. Several students also referred to the first year of university being the most challenging for daily time management.

Long-term time management

Four students with 11 coded references expressed to have experienced challenges regarding long-term time management, such as planning and scheduling single courses to the personal study plan. Three students experienced that earlier in their studies they had taken too many courses, for example in a single semester, due to their own decision or due to course scheduling by university. In addition, freedom to make personal study plans has been experienced challenging as three students express:

> *"Now in my third year in university, there has been so much freedom. One the one hand it's a good thing but on the other hand how and when and what I would choose. These kinds of questions have been quite stressful."*

> *"When I started it was easy because it was given for you on which courses to start. Now I have to schedule minor subjects all by myself so that has been more difficult."*

> *"It is your responsibility to schedule your studies. Sometimes it has been, for example this autumn when I started this academic year, it was like help what courses I could now take and what I should take."*

Also, one student experienced especially the first year in university overwhelming due to multiple softwares and systems that are used in studying.

5.1.2 Effort regulation

According to results, nine students out of ten had experienced challenges with effort regulation when facing distractions or uninteresting or challenging studies. Further, this main category included a total of 28 coded references, and was therefore one of the largest categories within students' challenges.

Uninteresting or challenging studies

Out of nine students, who responded to have challenges with effort regulation, eight students with 17 coded references expressed that challenges occur when facing uninteresting or challenging studies. The common way to act when facing such situations is to procrastinate or get distracted:

> *"I intuitively procrastinate as long as possible. And after that it feels even more challenging."*
>
> *"It happens quite often that I start using my phone and focus attention away from the* [uninteresting or challenging] *studies. This is how I unfortunately act in such situations."*
>
> *"Sometimes I just leave it undone or just procrastinate, that is a bad habit of mine."*

Studying at a more advanced level was experienced as one of the reasons for challenges in effort regulation: the requirements for different grades vary a lot between courses and sets therefore challenges to regulate effort accurately. Also, some courses may be so difficult to pass that the workload piles up which slows down the progression of studies. In addition, some students also reported to acknowledge the challenge, but not knowing how to make it better:

> *"I don't know, I should figure out a way how I would get myself to do also those unpleasant studies, for example uninteresting ones."*
>
> *"I have some courses that should have been completed during the first year in university, those which are not so interesting, and then I have procrastinated with them. - - I have three times registered to the course but never completed it and now it's time that if I want to graduate, I should really complete them."*

These results generally indicate that some students appear to have challenges with effort regulation such as procrastinating or getting distracted when facing uninteresting or challenging studies, for example studying at a more advanced level. These challenges may even lead to uncompleted courses if the student doesn't find a way to increase effort or be supported otherwise. However, most students still responded that after procrastinating for a while, some as long as possible, they would just force themselves to do it or otherwise increase effort, but failed to offer any clear strategy how they would do it.

Distractions

Seven students with 11 coded references responded to have challenges with effort regulation when facing distractions. Distractions then may lead to interrupting studying and therefore is located in the action phase. Generally students mentioned noisy surroundings and mobile phones to be the most distracting things. Also, students' responses varied according to the place where distractions happen: some responded to get more distracted when studying at home and some when studying at the university.

> *"At home it is easier to start doing other things such as watching Netflix but here at the university there are not such distracting things. And when I see others studying, I get motivated to start studying too."*

> *"At the university the biggest distraction is, -- friends who come to chat with me when they are passing by."*

However, as one student expressed, studying may partly happen by using technologies and therefore it may not be possible to just put them aside when studying. Generally, results in this subcategory indicate different preferences students have about studying and the place they tend to study.

5.1.3 Help seeking

Help seeking refers to individual's ability to control support of others, such as peers and instructors, and the ability to identify own needs for support and where to seek assistance (Pintrich, 1991). Interestingly, in this study only one student out of ten responded to have experienced challenges with help seeking. More specifically the challenge was linked to the ability to identify where to seek assistance and included only two references. This result was interesting because students had still experienced challenges and needs for support concerning other resource management strategies examined in this study. Because the result was this radical, I got interested in what kind of help seeking strategies students tend to use when facing challenges in their studies which may provide meaningful information about the reason why there is no challenges regarding this category compared to the other two resource management strategies.

Help seeking strategies

I divided the used help seeking strategies into two categories: tend to seek support outside and tend to independently deal with challenges. Eight students responded that they would first try independently deal with challenges for example by searching more information online or by using other strategies, such as lowering the set goals. However, if they did not manage to find solutions alone, all ten students responded to seek support outside when they face such challenges. The most common source where to first seek assistance was peers and if they did not manage to provide enough support, students in this study tended to lean on teachers and teacher tutors. Also the types of challenges define where to seek help:

> *"No matter what problem I have, I tend to first ask my friends for help. And if I don't get help there, I then contact teachers if the case is about a course or teacher tutor if the problem is linked to the progress of my studies."*
>
> *"If I would have any challenges, I would probably contact my teacher tutor. Anyways I would seek help outside but of course it depends if the challenges are linked to the specific courses or something else."*
>
> *"And if I have questions, of course I can contact the teacher in charge or my teacher tutor or course mates. So that you are never alone with your studies."*

Only one student, who experienced to have challenges with help seeking, responded that she would seek assistance outside, but at the same time she felt that there is no person with whom to discuss about challenges due to recent changes in guidance practices within university:

> *"There is no staff to ask because there is made changes within university. Previously all the staff has been available to single students but nowadays they are behind locked doors and it is recommended to e-mail study.education but they may never response. Then you have to try all by yourself to find someone to have conversation with. Also, when you go to the study centre, it has happened multiple times that they are not from your faculty and can therefore only give general advices."*

The results in this subcategory may explain why all students, except one, didn't experience challenges with help seeking: for students it appeared to be clear how to proceed when facing challenges and generally they didn't seem to hesitate about seeking assistance outside when they didn't manage to deal with challenges by themselves. However, this one experience concerning the lack of guidance staff indicates that there still may be students that are feeling "left alone" with their challenges even if they try to seek assistance outside.

5.2 Students' experiences of visualizations for recognizing challenges and needs for support

The second research question concerned what kind of experiences students had about the learning analytics visualizations in academic advising for recognizing their own challenges and needs for support. Table 2 demonstrates frequencies of coded references in each main category and also how they were distributed into positive and negative experiences.

Table 2. Students' experiences regarding visualizations

Main category	Positive (f)	Negative (f)	Total (f)
Time management	47	20	67
Effort regulation	20	24	44
Help seeking	36	2	38
Functionality and understandability	27	37	64
Total (f)	**130**	**83**	**213**

As table 2 presents, overall students' experiences were more positive than negative towards the used visualizations and their use in advising meeting for recognizing their challenges and possible needs for support. Majority of experiences regarded time management and functionality and understandability of the used visualizations. However, there were clearly mixed experiences in each main category except the help seeking, in which almost all experiences were positive.

5.2.1 Experiences regarding time management

Generally students experienced the visualizations and their use in academic advising more positive than negative in the perspective of time management. The results show that all ten students expressed both positive and negative experiences regarding this main category, but there is a clear difference with the amount of coded references in them. There are 47 references coded to the positive experiences and 20 references coded to the negative experiences.

Monitoring studies

Contents in this subcategory included experiences of how the used visualizations managed to support monitoring phase by visualizing the current situation of student's own studies. Experiences generally hold more positive than negative experiences when comparing both responses between students and the amount of coded references. For the first, all ten students mentioned positive experiences whereas four students mentioned also negative experiences. For the second, there were only six references coded to the negative experiences whereas 40 references were coded to the positive.

Nine students out of ten expressed directly that the current visualizations manage to support realizing what is already done and what is yet to come. Especially color-coding in bar chart was experienced positively. Positive experiences included also contents such as it motivates when you see progress concretely, and it makes easier to have conversations because it is made visible what courses are completed and what are not. Also, four students responded that the current visualizations provide a fast way for checking the general view regarding progression of studies:

> *"You get really good general view. At one glance you are able to view how you have succeeded with courses."*

> *"This radar chart especially managed to gather all courses together compared to the list in Weboodi. In Weboodi you have to visualize the general view yourself but these made it for you. It is now much faster to monitor what is your average grade when comparing to that list."*

Negative experiences, however, contained responses that visualizations would provide useful information especially for the teacher tutors but not so much for students themselves. In addition, negative experiences were linked to the use of these visualizations: two students considered that it failed to support any deeper analysis and the discussions were merely shallow and gave only descriptive useless information:

> *"We just looked quickly that these have been completed and these not, and not in detail for example by comparing different years."*

"It was just like explaining how these visualizations work - - so there were not any deeper analysis. Like I surely know how I have completed courses."

In addition to these, one student, who didn't use any visualizations in advising meeting, highlighted that conclusions regarding student's situation shouldn't be made based on just visualizations since there might be different reasons for uncompleted courses, and these reasons should be discussed before jumping to conclusions.

Planning and scheduling studies

Students had generally more negative experiences than positive regarding how visualizations managed to provide support for planning and scheduling future studies. The results were parallel when comparing both responses between students and references coded. Negative experiences included responses from eight students and twelve coded references, whereas positive experiences included responses from five students and seven coded references.

Six students responded that visualizations provide information based on last year, but fail to provide anything for future and therefore fail to support planning and scheduling future studies. In advising meeting, current visualizations also couldn't offer enough information for some students because student and teacher tutor had still to use Weboodi to view for example the estimated graduation time or to know what courses student should still complete in order to get the degree.

"These do visualize courses I have already taken but what about the personal study plan because we have planned to take courses with specific schedule. How they are going to be visualized or are they? Because it affects the planning of studies."

"Now it is visualized what is completed but after that you have to go to Weboodi to view what should still be completed."

Also, two students didn't consider grades as meaningful information regarding planning and scheduling future studies but expressed that it might be useful for students from other faculties when for example applying to minor subjects.

Positive experiences, in turn, included responses that current visualizations do manage to support planning for future studies because they visualize uncompleted courses and therefore can trigger considerations of how to reschedule them. Also, positive experiences included interesting responses regarding visualizations for supporting planning course selections and monitoring planning skills:

"With this radar chart you can view what kind of minor subjects would be good fit for you."

"Also you can view how well you succeeded to schedule courses in the first place before the new academic year starts. - - And how well it was clear for you in advance."

These results indicate that generally students didn't view current visualizations as supportive for planning and scheduling future studies since there were clearly more negative than positive experiences expressed. Also when comparing the amount of content in previous subcategory of monitoring studies, this subcategory clearly didn't raise that many experiences in the first place.

5.2.2 Experiences regarding effort regulation

According to results, students had mixed experiences regarding the visualizations and their use in academic advising in the perspective of effort regulation. Totally 24 references were coded to negative experiences and 20 references to positive experiences. Also, nine students out of ten expressed negative experiences and eight students expressed positive experiences.

Comparing studies to peers

This subcategory included experiences towards provided peer comparisons within radar chart and bar chart. Results show that this raised mixed experiences: eight students expressed negative experiences and five students positive. However the coded references were quite opposite: there were nine references coded as positive and 14 references coded as negative.

Four students considered peer comparisons as interesting new information. In addition, three students, who didn't use peer comparisons in the advising meeting, also considered such information interesting. Further, two of them would have wanted to use peer comparisons in advising meeting whereas one student wouldn't have.

"It would be helpful if there were grades and comparisons with every course so that you know how you have succeeded compared to peers. We for example had this course where 65% got grade one or failed or so, so grade three in that course would be more precious than same grade from some other course."

Four students experienced that the information regarding comparisons supports evaluating own performance compared to the perceived difficulty of the whole course. Some students also expressed that the use of peer comparisons raised positive emotions, such as it is relieving to notice that student is not the only one with uncompleted courses, and on the other hand, one student expressed that because he had succeeded better than average, it raises emotions of satisfaction. However, the use of peer comparisons raised also negative emotions and experiences, such as feeling defeated, and increased perceived pressure.

Three students from the Faculty of Education considered grades and peer comparisons as useless information since no one needs them for future studies in their faculty. In addition, one student, who didn't use visualizations in advising meeting, expressed directly that she would not want to discuss her grades with teacher tutor especially when the grade is compared to peers.

> *"I don't know how important it is in university to locate yourself to Gaussian distribution. That is more a high school thing."*

Evaluating effort

This subcategory includes evaluations regarding the use of effort when comparing to students own studies and success within them. Therefore this subcategory does not include evaluations based on peer comparisons because it was addressed in the previous subcategory. However, it should be acknowledged that seeing peer comparisons may have affected students' responses within this subcategory even though the contents themselves do not include them. According to results, also this subcategory included mixed experiences: negative experiences were expressed by five students and it included nine references, whereas seven students and 11 references were coded to positive experiences.

Five students responded that seeing own results concretely, especially if they were poor, would support increasing effort and pulling oneself together. Also, two students expressed that current visualizations can support regulating effort across courses because radar chart visualizes how student have succeeded. In addition, when changing the view to different academic years, it also supports monitoring:

> *"I can clearly see that these are my strengths and these I should continue to develop. I got better focus what I should do next."*

> *"And you could better compare different years, for example how the average grade has changed, if it got higher or lower.*

Negative experiences, however, included contents linked to perceived lack of meaningfulness regarding grades. Five students considered that visualizing grades do not provide useful information for them and do not help to regulate effort better. However only one of them, who didn't view any visualizations in advising meeting, was totally against visualizing grades since she considered grades as a subjective goals and wanted to keep the information private. The remaining four students expressed that grades did not provide useful information to them but they didn't care if they were used or not in advising meeting.

5.2.3 Experiences regarding help seeking

Even though students themselves in this study didn't appear to have challenges concerning help seeking, the results show that students considered current visualizations as supportive for help seeking. In fact, the result was quite radical: eight students and 36 references were coded as positive experiences, whereas only two students and two references as negative.

Recognizing needs for support and triggering conversations

Two students responded to have negative experiences concerning visualizations' ability to support help seeking and recognition of needs for support. However, one of them didn't use visualizations in advising meeting at all and that may be reflected to the answer: before responding there were long pause (10 seconds) and after that student answered:

> *"I don't know. At least they* [needs for support] *do not come up clearly from those."*

Also the response may be due to the fact that the student herself didn't have any major challenges with studies. Contents within positive experiences, in turn, included responses regarding the ability of visualizations to support recognizing needs for support especially for those who have challenges. Generally all eight students agreed that current visualizations would make visible the needs for support if they would have any. Because students in this study generally were well-achieving according to themselves, many expressed that especially other students, who would have more difficulties with studies, would benefit a lot from such visualizations:

> *"But if there is a student who has failed all five courses and didn't manage to complete them, then it can lead to the conclusions that there is need for support."*

"From this radar chart I would clearly see if there is some course with grade one compared to all other courses with higher grades. You don't necessary notice that in Weboodi because they are just listed there."

In addition one student, who reported that he has had difficulties with certain types of studies, considered meaningful that the graphs visualized it in the advising meeting. Also, six students experienced that the current visualizations did support conversations by triggering them and also guiding conversations to important themes:

"When you view what is completed and what is not, it opens a conversation for the possible needs for support. And then there is good chance to discuss and provide options for support."

"It is easier to get to the point when you have graphs to be monitored together. Compared to if one just have to explain."

"I was able to bring up things that in other advising meetings have not been discussed because they were just listed in Weboodi and therefore it looked like there is nothing to be worried out even though there perhaps was."

Feedback for high-achieving students

Generally all eight students considered visualizations as helpful especially for those who have difficulties with studies. However, well-achieving students in this study also expressed positive experiences regarding their own studies: their own thoughts about progression of studies were confirmed by noticing that they were on the right track, and seeing the results raised emotions of satisfaction and empowerment. The importance to get feedback about current status with studies was addressed in one response:

"That's the reason why I got there, to check with teacher tutor if my studies are on right track. Even though I have checked them myself but so that I am confirmed that it really is like that."

5.2.4 Experiences regarding functionality and understandability

Results indicate that students had mixed experiences regarding functionality and understandability of the visualizations. All ten students reported positive experiences and eight students negative. The coded references, however, located in the opposite way: there were 37 references coded as negative experiences and 27 as positive.

Functionality

Results show that there are mixed experiences between students: seven students had positive experiences whereas eight students had negative. However, the coded references varied with their amount: there were 24 references coded as negative and 12 references as positive. Positive experiences included responses related to preferences to overall using graphs instead of lists or texts and responses that included comparisons to Weboodi or Tuudo. Three students expressed directly that visualizations managed to provide information of studies better than Weboodi or Tuudo:

> *"It is more comprehensive than Weboodi. In Weboodi there is just long list of courses and then there is just grade after every row, so you don't get to know how others have succeeded."*
>
> *"In Tuudo there are also grades but they are also tabled just like in Weboodi, so maybe this is more productive."*

Negative experiences, in turn, were related to technical problems with the use of visualizations in advising meeting and also the perceived lack of meaningfulness regarding information they provided. According to students, the major technological problem was related to the use of Personal Study Plan (PSP) and some also expressed that the teacher tutor couldn't open student's visualizations at all. Six students expressed that they either haven't updated their PSP since the first year when it was compulsory to create it or they have several versions of it but left the original as their primary PSP. Because the information of the bar chart is derived from PSP, it led to the fact that it was not able to provide valid information for such students.

Understandability

There were mixed experiences regarding understandability of visualizations: negative experiences included six students and 13 references, whereas positive experiences included eight students and 15 references. Four students responded that they didn't have difficulties with interpretation of visualizations and they considered them as easily interpreted. Some, however, addressed that it took a while to interpret the radar chart and therefore there should be enough time provided for that. Also, they considered the explanation of teacher tutors as sufficient enough for creating understanding of the graphs.

Six students, in turn, had negative experiences and responded that they did have some difficulties with interpretation and some expressed directly that even teacher tutors didn't know how they should be interpreted and therefore weren't able to explain it to students. Bar chart was considered as easily interpreted, but especially interpretation of radar chart and peer comparisons were considered as difficult by those students:

> *"It remained unclear to me what this* [radar chart] *was. Are these like grades?"*
>
> *"Like those upper and lower quartiles, I think we have learned them in quantitative research course but I bet not many even understand them."*

5.3 Students' expectations for learning analytics to support their self-regulated learning and progression of studies

The third research question aimed to describe what kind of features students expected from learning analytics visualizations in order for them to benefit their self-regulation of learning and progression of studies. Table 3 demonstrates coded references of students' expectations for learning analytics. Therefore it gives information about how their expectations were distributed between main categories.

Table 3. Students' expectations for learning analytics

Expectations regarding	Expectations (f)
Time management	55
Effort regulation	12
Help seeking	6
Functionality and understandability	43
Total coded references (f)	**116**

As table 3 presents, the majority of students' expectations were linked to time management and functionality and understandability. Also similarly with results from other research questions, the least amount of coded references was linked to help seeking. Overall the amounts of coded references indicated that students held multiple expectations towards learning analytics and its use.

5.3.1 Expectations regarding time management

Generally results indicated that all ten students expected features linked to supporting time management. This is the largest main category including totally 55 references and therefore it may indicate that students overall can see the potential of learning analytics as supporting tool for time management and/or they otherwise consider such features as useful since they haven't got such support elsewhere.

Supporting long-term time management and monitoring studies

The results show that almost all students held expectations for supporting long-term time management and monitoring studies. This subcategory, including totally expectations from nine students out of ten and 30 coded references, is the largest subcategory within expectations for time management. According to students, in order to support long-term time management, learning analytics should visualize the planned studies and not only already completed ones. Some students expressed that they would benefit from creating schedules at the beginning of each academic year because it would also benefit monitoring how studies progress compared to the created schedules. Also at the end of the academic year, the system could send a situation report of how studies progressed compared to the original plan. In addition, because plans might change during academic year, it would be useful to be able to update those plans. If the planning tool is the already existing Personal Study Plan, it would be important to be able to switch between different created versions of it.

In addition, some students addressed that they would benefit from visualizations regarding how many courses are currently going on and what is yet to come in order to get the degree. Extension of color-coding would increase understanding: completed, planned and currently going courses should all have different colors. Also, it would be useful to add ECTS credits of each course. According to one student, that would also enable examinations of how much studying there is in periods and therefore enable considerations of how burdening studying might be. If there were some periods that contain vast amount of courses and some that don't, it would support planning them more evenly and therefore prevent possible exhaustion:

> *"It would support gaining a balance with your studies so that you wouldn't get it* [burn out]. *And also it would prevent having too little amount of studies so that there would be a good rhythm all the time."*

Supporting daily time management

Three students, with seven coded references, considered that they would benefit from features that support daily time management. Contents of expected features included the possibility to track study time which could support making knowledge-based decisions regarding studying. It would enable also tracking the used time for studying in different time frames, such as weekly or monthly views, and therefore support daily time management. Also it would enable evaluating the connection between used studying time and perceived course grade:

> *" - - and then you could see that generally you need this much time in order to get a certain grade. That would be interesting information to know."*

Other expectations concerned alarms that would support dividing studying into passages, such as alarming when it's time for a pause or time to continue studying. Also aggregating all the information of studies in one place would support using the time more efficiently since a student would be able to view clearly and quickly how the next studying hours should be used. Generally not that many students expressed expectations for supporting daily time management when comparing for example to expectations for supporting long-term time management. However, even with this sample size consisting only ten students, three of them expressed that they would benefit from such features.

Visualizing study modules and degree structures

Results show that eight students, with 18 coded references, expected features that would support visualizing study modules and degree studies. Expectations in this subcategory included contents that would support students to gain a sense of the whole regarding their studies. Generally students considered that visualizing modules besides or even instead of single studies would be more beneficial for them:

> *"It could count your average grades within different subjects and study modules. So not so much examining single courses but more larger entities."*

> *"And I immediately wished that there were views regarding different study modules, for example intermediate studies. I considered right away that it would be useful to view my grade averages and strengths."*

Also some students considered useful if there were degree structures visible because it would help to decide which studies were suitable as minor subjects and which as other studies. In addition, it would enable evaluations of how well studies have progressed as a whole compared to degree structures. Also, it would increase the acknowledgement of how many minor subjects and other studies should be completed in order to get the degree.

5.3.2 Expectations regarding effort regulation

Four students and 12 references were included in this main category regarding student expectations for effort regulation. Compared to the expectations of time management, these kinds of features were definitely not considered as beneficial among that many students.

Support for increasing and evaluating effort

Four students with 12 references were coded in this subcategory. The results indicate that students expected especially features that would provide support for increasing and evaluating effort. Two students expressed peer comparisons as meaningful features that would support evaluation of effort. One of them considered especially sufficient if it would contain also long-term comparisons, such as all students that have completed a certain course or comparison information from previous years and not only comparison information of students from same class. It would support evaluating the possible difficulty of a single course and therefore give information if increasing effort would be useful.

Also, two students considered it useful if teachers' evaluations regarding single assignments within a course would be available in the graph under each course. According to students, if there were arguments why certain grade is given, it would support evaluating already put effort. Also, outlook of all course grades would support noticing the total average grade more clearly and support making further evaluations if there were courses that need to be revised in order to increase the average grade point.

5.3.3 Expectations regarding help seeking

According to the results, four students had expectations regarding help seeking. Also, this main category generally included only six coded references, which resulted this being the smallest category within this research question. Generally students in this study didn't experience challenges with help seeking and also their experiences towards current visualizations for supporting help seeking were mainly positive which may be reflected in the results of this main category as well. However, four students still expressed expectations for help seeking and their expectations contained especially features that would support contacting personnel and also features that would work as a supportive tool for conversations in advising meeting.

Support for contacting personnel and interaction in advising meetings

Four students expected features that would support contacting the personnel and support interaction in advising meetings. One student considered useful if there were contact information of teachers in charge from different courses made available and easily contacted via one click. However this raised also concerns regarding privacy issues:

> *"Of course the teacher in charge should only be able to view student's information of that specific course and only teacher tutor could view all information."*

In addition, two students had expectations regarding advising meetings. One student expressed that it would be supportive if the system would show information about the date of the last meeting with teacher tutor and if it would provide reminders to book a meeting at least once a year. Other student expressed that if there were visualized information including registrations to courses, it would support conversations with teacher tutor:

> *"If it was clearly made visible, it would trigger questions of the reasons why specific course is still uncompleted. For example if there are difficulties or other reasons behind it."*

5.3.4 Expectations regarding functionality and understandability

According to the results, nine students' responses contained expectations regarding functionality and understandability of visualizations and their use. This is the second largest category within this node including a total of 43 references. One possible reason for that may be that according to the students, there were some problems regarding their use and interpretation of graphs in advising meeting.

Supporting functionality

Nine students with 37 coded references expected features that would support functionality of visualizations and their use. Students' expectations in this subcategory generally included contents of sources where the graphs could derive their information, meaningful messages and automated alerts from learning analytics, and proper platforms for visualizations in the future. Four students considered important that the current problems with visualizations regarding the use of Personal Study Plans as a base would be solved in order to increase the validity of visualizations. There were suggestions that maybe they could be based on other information in Weboodi, such as course registrations, or if the information has to be derived from PSP, there should at least be options to switch what PSP is used. Also, one student expressed that it would be helpful if the system could take information also from studies in other universities.

Generally seven students considered useful to get notifications and messages from learning analytics. However all, who wished such features, addressed that messages should include only meaningful information and they would like to receive only the most necessary ones. There were multiple preferences concerning what is perceived important enough for sending alerts and what not. Meaningful notifications included alerts regarding how well student has succeeded compared to previously made schedules and set goals. Also, one student considered useful to receive alerts regarding daily time management, such as how many hours student should study in order to achieve previously set goals for studying hours. One student, in turn, considered it useful to receive alerts regarding long-term time management, such as if the student was falling behind compared to previously set goals for progression of studies. Also reminders to register to courses were considered as meaningful.

Some weekly checkups or notifications for new grades, however, were considered as useless. Two students also expressed directly that they would prefer not to receive any distinct alerts or messages from learning analytics:

> *"More so that I would be aware of the existence of such tools and I would know how to access them."*
>
> *"I prefer my everyday life not to be disturbed with such messages. More so that they are only within the app."*

Six students expressed that the proper platform could be some application. Three of them considered especially Tuudo as a proper platform because they tended to use it actively. Also according to students, if there were learning analytics, they should be as easy to use as possible and function properly with using both mobile and computer. In addition, one student addressed that it would be helpful if the systems used in studies were sharing information automatically between each other:

> *"If teacher sets deadlines for assignments in Moodle, why I have to transfer them one by one to Tuudo's calendar? It feels stupid that students have to stress such trivial things which could be fixed easily."*

Supporting understandability

Four students with six coded references expected features that would support understandability. Three students' expectations addressed adding guides and definitions to support interpretation of visualizations, such as defining upper and lower quartile and the comparison information more clearly and adding explanations. Also, one student considered the radar chart too difficult to interpret and suggested that maybe there could be some other graph instead.

5.4 Summary of the results

The intention of this chapter is to summarize and bring together results from all research questions in order to form an understanding of the whole. The results indicate that students in this study didn't generally have any major challenges or needs for support concerning resource management strategies and studies. The main challenges regarded time management and effort regulation, whereas help seeking didn't include almost any challenges. Further examinations revealed that students tended to use clear help seeking strategies when facing challenges: majority would first try by themselves and after that seek assistance outside if they didn't manage to solve the challenge alone. Main challenges linked to time management were temporary challenges with daily time management when there were multiple deadlines or otherwise lots to do and too little time left. Majority of challenges related to effort regulation, in turn, included procrastinating or getting distracted when facing uninteresting or challenging studies. Many students, however, addressed that their challenges were only temporary and they generally hadn't affected the progress of their studies.

The results indicated that even though there were more positive than negative experiences, all students had mixed experiences regarding current visualizations and their use in advising meeting. Similarly with the first research question, help seeking raised generally the least amount of experiences compared to other categories and almost all experiences regarding it were positive. Therefore, the distribution of students' responses in it differed from other categories. Generally students' positive experiences concerned the ability of visualizations to make challenges and needs for support more visible and therefore provide support for conversations in advising meeting. Also, students experienced positively its ability to support monitoring studies and generally the whole idea of visualizations was considered as welcoming a new opportunity besides already existing systems.

At a general level, negative experiences concerned current visualizations' failure to support planning future studies and furthermore failure to provide meaningful new information. Because of that, some did even consider the current visualizations more helpful for teacher tutors than themselves. Also, there were technical problems for example with use of PSP as a base of bar chart, which led to the conclusion that studies it should have visualized were not valid and updated. Radar chart and peer comparisons were also experienced as difficult to interpret in advising meeting by some students. In addition, overall the use of peer comparisons and grade information raised lots of mixed experiences: some did consider it meaningful and some did not. Table 4 summarizes more in detail what kind of contents students' positive and negative experiences in each subcategory included.

Table 4. Students' experiences of visualizations for recognizing challenges and needs for support

Students' experiences regarding		Positive experiences	Negative experiences
Time management	Monitoring studies	- Manages to visualize completed and uncompleted courses well -Color coding were perceived useful -Fast way to check overall view -Seeing progression of studies increases motivation	-Doesn't provide new meaningful information -Only descriptive information -Doesn't support deeper analysis of progression of studies
	Planning and scheduling studies	-Triggers considerations how to schedule uncompleted courses -Provides support for evaluating planning skills -Supports future course-selections	-Lack of visualized information regarding future studies -Doesn't visualize how much courses are left to get the degree -Doesn't provide information of the estimated graduation date
Effort regulation	Comparing studies to peers	-Provides interesting new information -Manages to raise positive emotions such as reliefs and satisfaction	-Not considered as meaningful and useful information -Raises negative emotions such as feeling defeated and pressured
	Evaluating effort	-Supports increasing effort and pulling oneself together -Triggers also regulation of effort and monitoring	-Not all students considered grades overall as equally important information
Help seeking	Recognizing needs for support and triggering conversations	-Makes needs for support visible -Triggers and guides interaction in advising meeting	-Needs for support could be more clearly visualized
	Feedback for high-achieving students	-Confirms own thoughts -Raises positive emotions such as empowerment and satisfaction	-Doesn't provide crucial information for high-achieving students
Functionality and understandability	Functionality	-Preferences to use graphs over lists or texts -Perceived better than already existing tools	-Technical problems especially with PSP -Doesn't provide meaningful information
	Understandability	-Some students considered all graphs as easy to interpret -All students considered bar chart as easy to interpret	-Didn't get enough support for interpretation in advising meeting -Radar chart more difficult to interpret

Table 5, in turn, presents and summarizes contents of students' expectations for learning analytics in each category. Generally there were more expected than unexpected features included due to students' focus to express more expected features. Results indicated that students had, first of all multiple, but also different expectations for learning analytics which sometimes were even controversial. Furthermore, results indicated that because students expect different things from learning analytics, they also consider different things as meaningful for them and their studies. Majority of students' expectations regarded long-term time management and monitoring studies and functionality and understandability. Many also expected visualizations of larger entities than just single courses because it would make the progression of studies more visible. Similarly as with other research questions, help seeking raised the least amount of expectations.

One interesting and important finding is that instead of using learning analytics only in advising meeting, students would like to have independent access to it. This was addressed directly by only few students but indirectly by contents presented in table 5. For example tracking study time and creating schedules or being able to view teachers' evaluations of single assignments within courses clearly can be interpreted so that students' expectations regarded situations outside the advising meeting.

Table 5. Students' expectations for learning analytics

Main category	**Subcategories**	**Students' expectations**
Time management	Daily time management	-Possibility to track study time with different time frames such as weekly and monthly views -Alarms to support dividing studying into passages, such as pausing and continuing studying -Connecting all information regarding studies in one place
	Long-term time management	-Visualizing also planned studies -Ability to create individual schedules -Receiving situation reports of how studies progress compared to the individually made schedule -Adding information of ECTS credits -Color coding for completed, planned and currently going on courses -Adding information of how many studies has to be completed in order to get the degree
	Visualizing study modules and degree structures	-Adding degree structures -Visualizations of larger entities than just single courses, such as different study modules
Effort regulation	Increasing and evaluating effort	-Peer comparisons from longer period of time, such as comparison information from previous years - Teachers' evaluations of single assignments within courses available to the graphs -Outlook of all course grades
Help seeking	Contacting personnel and supporting interaction in advising meeting	-Adding contact information of teachers in charge from different courses - Adding information of the last advising meeting date and provide reminders to book a meeting for example once a year -Supporting advising conversations by including information of registrations to courses
Functionality and understandability	Functionality	-Replacing PSP for some other information in Weboodi or options to choose which PSP is used - Customizable notifications and automated alerts - Tuudo or some other application as a platform - Individual access to visualizations - Suitable for both mobile- and computer use
	Understandability	-Guides for supporting interpretation - Definitions of upper and lower quartile - More clear explanations for comparison information

6. Conclusion and discussion

The focus of this thesis was at the intersection between learning analytics and self-regulated learning where academic advising worked as a context, but the main goal was to provide insights how self-regulated learning can be supported via learning analytics according to students themselves. This therefore limited the examination to the microanalytic layer and especially to university students' perspective. Students' perspective is particularly important for the reason that there is an underlying assumption that providing learning analytics information to students is sufficient enough to enhance their self-regulated learning (Howell et al., 2018). Also academic advising provides meaningful context because it is known to have an effect on students' progression of studies and performance (Ali-Ansari et al., 2015; Young-Jones et al; 2013) but is not yet researched enough in learning analytics contexts (Charleer et al., 2018).

More specifically I focused on finding answers to three separate research questions by interviewing ten second and third year students, and analyzing their responses via qualitative theory directed content analysis. In semi-structured interviews, self-regulated learning was measured as an aptitude (Winne & Perry, 2000; Winne, 2010). Also, the examination of this thesis was limited to self-regulation of behavior that is defined as individuals' ability and attempts to control their overt behavior (Pintrich, 2000) and further to three resource management strategies; time management, effort regulation and help seeking presented in Motivated Strategies for Learning -Questionnaire (Pintrich et al., 1991).

First research question included examining what kind of challenges and needs for support students in this study had concerning resource management strategies and progression of studies. Results indicate that majority of students' challenges and needs for support were linked to time management and effort regulation and within those especially daily time management and uninteresting or challenging studies. Even though the students reported that challenges generally hadn't affected their progression of studies in the long run, they seemed to appear for example as negative emotions, procrastination or as lack of scheduling skills when planning and for some students, lead even to uncompleted courses. According to the sociocognitive view, self-regulated learning varies not only between individuals but also within individuals (Duncan & McKeachie, 2005; Credé & Phillips, 2011). This view got support from the findings in this research: even though students experienced that they could self-regulate their learning well, challenges appeared with self-regulation when studies weren't that interesting or easy to handle.

In addition, it was interesting that when comparing what to daily time management, it appeared to be viewed as students' own responsibility, whereas long-term time management was made easier for student when starting university studies for example by giving courses where to begin with. Still, results of this study indicate that students have to plan and schedule their personal study plan sooner or later in their studies, which might then raise stressful feelings, and may lead to challenges, such as taking too many courses on a plate. Therefore it would be important to ensure providing support at least for those who need it especially during the first year in university – perhaps not everyone has developed the skills sufficient enough to complete with so much independent work. Students' general positive attitudes towards learning analytics especially for supporting time management may indicate that it would be reasonable to consider learning analytics as such supportive tool.

Second research question included what kind of experiences students had about learning analytics visualizations in academic advising for recognizing their challenges and needs for support. Students had more positive than negative experiences of visualizations, which may reflect students' positive attitudes towards learning analytics. However, there were still mixed experiences in each main category except help seeking, in which almost all experiences were positive. Because there generally were mixed experiences in each main category, it leads to the conclusion that current visualizations didn't manage to support students' self-regulation as efficiently as they could.

Generally, students considered visualizations helpful for monitoring studies. If students had more challenges with studies, the visualizations would make challenges more visible and therefore also trigger conversations in advising meeting. For high-achieving students, visualizations can provide confirmations of being on the right track and motivate to keep on the good work. These results are in line with previous research findings indicating that learning analytics can lead to positive outcomes such as improvements in engagement, connection and motivation (Verbert et al., 2014).

However, it is also presented that in order to develop efficient learning analytics, its feedback should include all levels of learning: where and how student is performing and where he/she should head next (Matcha et al., 2019) and therefore include features from each phase of self-regulation (Schumacher & Ifenthaler, 2018; Sedrakyan et al., 2018). Findings of this study indicate that this clearly doesn't happen with current visualizations: according to students' responses, current visualizations generally manage to support monitoring already completed studies but fail to provide support for planning future studies. With this regard, results of this study differ from the previously in academic advising developed dashboard LISSA, which managed to provide insights into students study progress and support future study planning (Charleer et al., 2018). Results of this study provide support only for the former result but not for the latter.

That, however, seem to be common challenge in many already existing dashboards, since many of them focus on providing performance oriented feedback, such as how a student is performing, instead of process-oriented feedback focusing on how a student could perform better (Sedrakyan et al., 2018). Also, it is suggested earlier that the low perceived usefulness might stem from the focus of using only descriptive learning analytics instead of providing also predictions (Park & Jo, 2015), which might be the case also in this research.

It is also presented earlier that providing peer comparisons, such as group averages, are commonly used in many learning analytics dashboards (Matcha, 2019; Schwendimann et al., 2017) but they may not be suitable for everyone (Sedrakyan et al., 2018). In this study, there were overall mixed experiences regarding peer comparisons: some did view it as interesting new information that is not provided them before and others did view it as useless or even experienced negative feelings such as pressured or feeling defeated. Results in this study therefore provide support to previous research indicating that perceived negative feedback given by learning analytics may raise mixed experiences and lead to negative emotions and experiences between students (Roberts et al., 2016; Howell et al., 2018).

Despite the mixed experiences, results of this study also provide overall promising results: the use of current visualizations in advising meeting has the potential to detect possible needs for support and provide chances to discuss about options for support before the challenges lead to more severe difficulties. The use of learning analytics may therefore add value to the advising meeting and to already existing systems especially for those students, who have more challenges or who may not have yet acknowledged them. However, some students still considered visualizations more meaningful for teacher tutors than themselves since they failed to provide any new information for students. Previously for academic advising developed dashboards LISSA (Charleer et al., 2018) and LADA (Gutiérrez et al., 2018) also appeared to be especially helpful for teacher tutors, and with this regard, results of this study seem to be similar.

These experiences of visualizations not being meaningful for students themselves may, however, be partly affected by technical problems with their use that many students also reported. The main problem concerned the use of Personal Study Plan as a base of bar chart since not many students even used PSP in the first place. This led to the fact that it failed to provide updated information of student's studies. Also there were challenges with interpretation of the graphs in advising meeting: not all teacher tutors managed to support interpretation sufficiently enough. Especially radar chart and comparison information were experienced as more difficult to interpret, and more support for interpretation would have been needed. It is noted also earlier that students may have difficulties in the interpretations of graphs (Park & Jo, 2015) and therefore organizing training that supports interpretation is necessary (West et al., 2020). The results in this study reflect overall the need for further educating all stakeholders how to interpret learning analytics correctly. In addition, I suggest that in AnalyticsAI it would be reasonable to create additional guides for interpretation, especially if in future students have individual access to the visualizations.

Third research question included what kinds of features students expect from learning analytics in order them to benefit their self-regulated learning and progression of studies. It is presented previously, that for students ideal learning analytics tool would provide information that supports them to better self-regulate their learning (Roll & Winne, 2015) and therefore learning analytics should provide only meaningful feedback and not just any information that is available (Matcha et al., 2019). Results of this study indicate that students had different preferences regarding what information they considered meaningful and what would support their self-regulation. Therefore they also had different expectations for learning analytics, which sometimes were even controversial. These results are again in line with previous research (Schumacher & Ifenthaler, 2018; Roberts et al., 2017).

Similarly as with experiences, results indicate that majority of students' expectations were linked to time management and functionality and understandability. Generally students expected to get more support for planning phase, such as possibility to create individual schedules and receive situation reports of how studies have progressed compared to the original schedule which would also support monitoring studies. These expectations provide interesting continuum for previously mentioned experiences indicating that current visualizations fail to support planning. Generally these results may also reflect problems with the current planning tool PSP as it appears that it doesn't manage to support long-term time management sufficiently enough and there is need for other supportive features regarding it. Providing support to planning phase would be important also in the perspective of self-regulation: in order to support self-regulated learning efficiently, learning analytics systems should include features from each phase of self-regulated learning (Schumacher & Ifenthaler, 2018). Because of all the aforementioned, I suggest that when further developing the visualizations in AnalyticsAI, it would be important to make sure the visualizations include feedback from all levels of self-regulated learning.

Also, majority of students generally expect visualizations of larger entities more than - or even instead of - just visualizing single courses, because it makes the progression of studies more visible, and therefore supports students to gain a sense of the whole. However, these findings may result from the fact that students in this study didn't have any major challenges with progressing in their studies, and therefore they may not have considered it as meaningful to visualize smaller entities, such as single courses, as some students, who would have more challenges. Also it is interesting, that even though the majority of students' challenges regarded daily time management or studying in uninteresting or challenging tasks, there were not that many expectations towards those themes. This may indicate that students in this study just generally didn't view supporting effort regulation or daily time management as necessary as supporting for example long-term time management.

It is presented previously that it is typical to start with descriptive analytics but eventually it is expected to add also other dimensions, such as predictions (Park & Jo, 2015). Expectations regarding predictions were not addressed by students in this study, but other dimensions, for example the possibility to track study time via learning analytics, however, were presented by few students. Interestingly, this might provide support to previous research indicating that instead of predictive methods, learning analytics may be evolving towards a deeper understanding of individuals' learning processes and experiences (Viberg et al., 2018). On the other hand, it may be that students in this study were not familiar with all the possibilities that learning analytics can enable.

Further, the results of this study indicate that because students expect different things from learning analytics, it may be reasonable to create customizable learning analytics, which is suggested also in previous studies (Roberts et al., 2017). Also, one interesting and important finding is that instead of using learning analytics only in advising meeting, students would like to have independent access to it. In previous research, the potential key for acknowledging individual preferences is to support students' agency and control over learning analytics by allowing students themselves to choose what data they want to include or exclude and how it is used and reported back (Knox, 2017; Roberts et al., 2017). I suggest that adding this kind of function would be reasonable to consider in AnalyticsAI as well, since it would provide a solution for developing individually meaningful learning analytics.

Addressing students' agency is also in line with theories of self-regulated learning (Pintrich, 2000). In this study, however, teacher tutors had the possibility to decide what graphs were viewed in the advising meeting and therefore students' agency was not fully supported. Actually, some students even responded that they expected learning analytics to provide peer comparisons but teacher tutors had decided to exclude those graphs in the advising meeting. This may indicate that perhaps some teacher tutors shy using such information with students, but this needs further researching in order to understand their decisions. There were also opposite expressions: not all students in this study were even willing to use all visualizations with their teacher tutor and that would be important to take into consideration, as previous research also have addressed (Schumacher & Ifenthaler, 2018). These results overall highlight the same conclusion as previous studies: it is necessary to examine students own thoughts and expectations instead of just having assumptions of it (West et al., 2020). Future research should therefore continue examining how to develop learning analytics in a way that is perceived useful by students themselves.

Even though the results of this study provide interesting insights into learning analytics from students' perspective, the results of this thesis should be viewed through its limitations. Firstly, participating students were searched through an e-mail sent by the teacher tutors and then the volunteered students expressed their willingness to participate in this study. Results of the first research question also indicate that the participating students were a selected group of well-achieving students whose challenges generally hadn't affected their progress in studies. It may be that students with more challenges didn't even want to participate in the first place. Therefore results of this study don't apply for lower-achieving students and future research should include more heterogenic group of students. Secondly, students reported to have viewed different amounts of graphs in advising meeting: two students didn't view any graphs, five students viewed all and three students viewed all except comparison information. These differences may have affected to students' interview responses.

There are also limitations regarding the use of semi-structured interviews and qualitative content analysis as research methods. Knowledge produced in interviews is contextual and its objectivity should be viewed through subjectivity (Kvale & Brinkman, 2015). My own position as a student and at the same time as an interviewer, and the fact that interviews involve always interaction, lead to the conclusion that I inevitably have affected to the interview process and therefore also may have affected on students' responses. In addition, interviews and qualitative content analysis involves always interpretation (Kvale & Brinkman, 2015; Schreier, 2012; Hsieh & Shannon, 2005). According to Hsieh and Shannon (2005) the coding process defines the success of whole qualitative content analysis so it is especially important that the coding, and interpretation involved in it, is done as carefully and as transparently as possible. In order to support transparency of interpretation and evaluation of this study, I have tried to describe in great detail how the coding process progressed step by step, and I took several coding rounds to make sure the coding was done as carefully as I could. In order to increase the reliability of coding, I also assessed the inter-coder reliability with other coder, which indicated that the percentage of agreement was relatively high (92%). However, the results of this study should still be examined critically by keeping its limitations in mind.

Because the context of this thesis was dated on pilot study conducted in AnalyticsAI, in which the used visualizations are yet under development and appropriate practices are just forming, future research should examine students' experiences also after the development process. Previous research of learning analytics in higher education has shown that there is so far only little evidence indicating improvements in learning outcomes (Viberg et al., 2018) and therefore future research should also focus on whether the system can create actual impacts on students' learning. I suggest that researching students themselves would be a potential way to obtain such information, and especially examining whether the system have managed to create impacts on self-regulated learning, since it is known to play a crucial role on student performance (Zimmermann, 2002). However, I believe that overall the findings presented in this thesis can provide meaningful information for future development of learning analytics and its use in higher education institutions especially in the perspective of one of its main stakeholders: students themselves.

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Appendix 1: Interview Protocol

General questions and progression of studies

1. What kind of experiences do you have about studying in university?
2. When you have experienced your studying to be easy and when challenging?
3. How the collaboration with your teacher tutor has gone?
4. What kind of goals do you have concerning studies?
5. How would you describe your progression of studies when comparing to your goals for studies?
6. Could you describe your typical study week for example in this period?
   6.1 What kind of learning situations it more specifically contains? (Lectures, group work, independent work, digital learning environments)
   6.2 What kind of learning environments and tools do you use when studying?
   6.3 What is effective learning in your opinion?

Resource management strategies

7. How do you schedule your studies on a daily basis?
8. Have you had challenges concerning scheduling your studying? What kind of challenges?
   8.1 Do you experience the need for support to schedule and manage your time concerning studying? What kind of support?
   8.2 What enhances the effective use of scheduled time for studying?
9. How do you act in a situation if the learning is uninteresting or if the task is difficult?
   9.1 How do you motivate yourself to study if the task is uninteresting or difficult?
10. How do you act when facing difficulties in your studies?
    9.1 In what kind of situations you have sought/would seek help in your studies?
11. Where would you seek help if your studies didn't progress the way you planned?
    9.1 What kind of support do you seek from lecturers or teachers? From peers? From teacher tutor?

Experiences regarding learning analytics visualizations

Version 1: For those who have used the visualizations in academic advising meeting

12. Did you take a look at all the visualizations introduced here?

12.1 If not, did the teacher tutor offer you the opportunity to view them? Could you think the reason why it was/was not offered?

13. How did you go through the visualizations in advising meeting?
14. How did you experience the advising meeting otherwise?

    14.1 Was it similar compared to your earlier advising meetings?

15. Did you get support in that advising meeting for enhancing the progress of your studies?

    15.1 What kind of impression did you have after the advising meeting about your progression of studies and how you can have an influence on them?

16. What kind of information did the visualizations provide to you during the advising meeting?

    16.1 How did you experience the visualizations compared to earlier views for example in Weboodi?

    16.2 What kind of information and features these visualizations should provide to you so that you consider them to be meaningful to your studying and progression of studies?

17. How did the visualizations effect the conversation with your teacher tutor?
18. What kind of feelings did you have when you saw/used these visualizations for the first time?
19. Did these visualizations provide support during the advising meeting in your opinion? What kind of support?

    19.1 Did these visualizations have disadvantages during the advising meeting?

Visualizations and resource management strategies

20. These visualizations aim at making the progression of studies and the possible need for support more visible and therefore easier to have a conversation during the advising meeting. How did this definition work in your opinion?

    20.1 How did you consider the scheduling and time management of studies to become visible?

    20.2 How did you consider planning and reflecting your actions become visible?

    20.3 How did you consider the questions concerning the need for support and getting support become more visible?

21. Is there something you don't want to use these visualizations? If yes, what?
22. Do you wish these visualizations to give you notifications? What kind of notifications? What kind of notifications you don't wish?
23. Is there anything else you want to say or add to this interview?

Version 2: For those who have not used visualizations in advising meeting

Did you take a look at these visualizations introduced here or did you take a look at some other tools such as Weboodi?

12.1 Did the teacher tutor offer you the opportunity to view them? Could you think the reason why it was/was not offered?

13. How did you experience the advising meeting otherwise?

    13.1 Was it similar compared to your earlier advising meetings?

14. Did you get support in that advising meeting for enhancing the progress of your studies?

    14.1 What kind of impression did you have after the advising meeting about your progression of studies and how you can have an influence on them?

15. What kind of information do these visualizations provide to you?

    15.1 How do you experience the visualizations compared to earlier views for example in Weboodi?

    15.2 What kind of information and features these visualizations should provide to you so that you consider them to be meaningful to your studying and progression of studies?

16. How these visualizations would effect the conversation with your teacher tutor?
17. How does it feel to see these visualizations?
18. Would these visualizations provide support during the advising meeting in your opinion? What kind of support?

    18.1 Would these visualizations have disadvantages during the advising meeting?

Visualizations and resource management strategies

19. These visualizations aim at making the progression of studies and the possible need for support more visible and therefore easier to have a conversation during the advising meeting. How would this definition work in your opinion?

    19.1 How do you consider the scheduling and time management of studies become visible?

    19.2 How do you consider planning and reflecting your actions become visible?

    19.3 How do you consider the questions concerning the need for support and getting support become more visible?

20. Is there something you don’t want to use these visualizations? If yes, what?

21. Do you wish these visualizations to give you notifications? What kind of notifications? What kind of notifications you don’t wish?
22. Is there anything else you want to say or add to this interview?