Aalto University
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Design Guidelines for Future Procurement Analytics Software

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Abstract

This Master's Thesis addresses the future of the design of procurement analytics software. Amidst pressure from a competitive market, procurement analytics providers need to differentiate against competitors and increasingly intelligent do-it-yourself-solutions. The goal of this thesis is to identify key design guidelines for future procurement analytics by identifying the important future features and discussing how they should be designed.

Incorporating evidence from a literature review and interviews with Sievo's, a Finnish procurement analytics provider, customers and employees, the thesis implies that artificial intelligence (AI) driven features as well as live data integrated to external applications are notable factors of procurement software's future.

The results of the research show that designers going forward need to design AI-features for human override and control as default. AI agents should operate alongside human employees, with the possibility for human users to customize the extent of AI-driven operations. In addition, people should be able to take over and override AI-made recommendations and decisions to mitigate potential errors' impact. Such control will lessen user resistance and enhance users' trust in the AI-features.

In addition to users' control of AI, transparency is a usability requirement of AI-driven features. Users should be able to view the reasoning behind AI-offered insights and be kept within the loop of AI executed actions. This way, they are more likely to be able to trust the recommendations and actions made by the AI which enhances its user experience and adoption.

Finally, integrated platforms and real-time data should be treated as accessibility contributors. Integrating an AI-agent to platforms the users already use would enable them to inspect data using natural language, whenever and wherever they are. In the case of global disruptions, such as natural disasters, the software could help the users by offering near immediate speculative scenarios relating to the recent event, helping them to take appropriate action in time.

Keywords Procurement analytics, design guidelines, user experience, future design

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Tiivistelmä

Tämä Diplomityö käsittelee hankinta-analytiikkaohjelmistojen suunnittelun tulevaisuutta. Alan kilpailun aiheuttaman paineen keskellä hankinta-analytiikan tarjoajien on erottauduttava kilpailijoistaan sekä yhä älykkäämmistä tee-se-itse-ratkaisuista. Tutkielman tavoitteena on tunnistaa keskeisiä suunnitteluohjeita tulevaisuuden hankinta-analytiikalle määrittämällä tärkeät tulevaisuuden ominaisuudet ja pohtimalla, miten ne tulisi suunnitella.

Kirjallisuuskatsauksen sekä Sievon, suomalaisen hankinta-analytiikan tarjoajan, asiakkaiden ja työntekijöiden haastattelujen pohjalta tutkielma osoittaa, että tekoälyyn (AI) perustuvat ominaisuudet sekä reaalikaikainen data ulkoisiin applikaatioihin integroituna ovat merkittäviä tekijöitä hankintaohjelmistojen tulevaisuudessa.

Tutkimuksen tulokset osoittavat, että suunnittelijoiden tulee jatkossa kehittää tekoälyominaisuuksia siten, että ihmisellä on oletusarvoisesti mahdollisuus ohittaa ja hallita tekoälyn toimintaa. Tekoälyn tulisi toimia ihmisten rinnalla, ja käyttäjien tulisi voida mukauttaa tekoälypohjaisten toimintojen laajuutta. Lisäksi käyttäjien tulisi voida ohittaa tekoälyn suosituksia ja päätöksiä mahdollisten virheiden vaikutusten vähentämiseksi. Tällainen hallinta vähentää käyttäjien vastarintaa ja lisää heidän luottamustaan tekoälyominaisuuksia kohtaan.

Käyttäjien tekoälyn hallintamahdollisuuksien lisäksi läpinäkyvyys on tekoälypohjaisten ominaisuuksien käytettävyyden vaatimus. Käyttäjien tulisi voida nähdä tekoälyn tarjoamien näkemysten perustelut sekä pysyä ajan tasalla tekoälyn suorittamista toiminnoista. Näin käyttäjät todennäköisemmin luottavat tekoälyn tekemiin suosituksiin ja toimenpiteisiin, joka kohentaaa sen käyttökokemusta ja käyttöönottoa.

Lopuksi, integroituja alustoja ja reaaliaikaista dataa tulisi kohdella saavutettavuuden tekijöinä. Tekoälyagentin integroiminen alustoihin, joita käyttäjät jo hyödyntävät, mahdollistaisi datan tarkastelun helposti, luonnollista kieltä hyödyntäen, ajasta ja paikasta riippumatta. Maailmanlaajuisissa häiriötilanteissa, kuten luonnonkatastrofeissa, ohjelmisto voisi tukea käyttäjiä tarjoamalla lähes välittömiä spekulatiivisia skenaarioita tapahtumaan liittyen, mikä auttaisi heitä toimimaan ripeästi.

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To the friends I gained along the way, thank you. You mean more to me than you know, and have taught me more than any school ever could. Here's to the good times ahead and life lessons to come!

Thank you to Sievo, for being an awesome employer for students, letting them explore career options and find their passions, like I did. Special thanks to the design team, who took an inexperienced developer under their wing and nurtured them into a designer.

Thank you professor Marjo Kauppinen and my instructor Heini Jokinen for your guidance during the thesis process. You provided excellent support and patience, without which this thesis wouldn't have been made. And, thank you Pawel, for keeping me sane through exercise and reminding: "*don't overkill it*".

Thank you to my parents for raising me and giving me the opportunity and privilege to try, succeed and fail (safely!) in all my endeavors. Thank you to my sisters, too, for constant life inspiration, emotional support and furniture advice.

I have the best friends in the world, a loving family, a wonderful home, a job I thoroughly enjoy, I am healthy and stronger than ever to boot. Aina voi mennä huonommin!

Näetkö tuon vanhan pihan aidan?
Näetkö mitä siel on takana?
Siel on laskut, remppa, lapset, asuntolaina
Ja tuhat murhetta niin kuin sinulla

Helsinki,14 September 2025

Anna E. Ruikka

Contents

Abbreviations

HCI	Human-Computer Interaction
UX	User Experience
AI	Artificial Intelligence
GenAI	Generative Artificial Intelligence

1 Introduction

1.1 Background and motivation

Sievo is a Finnish procurement analytics company. Since its founding in 2003, the company has grown to over 400 employees and has offices in Europe and the U.S. The company's product aims to help its customer companies to track and manage their spend, optimize overall procurement processes and aid data-driven decision making.

Today, the state of procurement analytics software is largely dashboard oriented. It is up to the user to depict the relevant insights from the data and take action. The CEO of Sievo Sammalkorpi, S. (2024) stated that *"Analytics has zero value. It's the actions that drive the value"*. There is strong incentive to shift Sievo's product design and user flow away from dashboards and towards guided flows, ready insights powered by artificial intelligence (AI) and meaningful actions provided by the software.

Sievo is not alone in realizing the shift from dashboard oriented software towards an intelligent, actionable one. For example, the paper put forth by Easton, Epstein & Shen (2019) recognizes the shift, describing the future of procurement analytics as relying on automatically generated, AI-enabled insights. Amidst increasing pressure from a competitive market, retaining advantage through differentiation is key. Sievo needs to be able to win against other procurement analytics companies as well as do-it-yourself-solutions like PowerBI. Being ahead of the curve and leveraging state of the art technology while upholding outstanding user experience will support more customer up-sales and retention, which in turn ensures the financial success of the company and its stakeholders.

Sievo has recognized the importance of the upcoming shift in analytics, and has even started to take action in developing AI-powered features and other future incentives. However, there are still uncertainties about what exactly are the most important future development targets for the users and what should be taken into account when designing these new features. This Master's Thesis' goal is to help with these issues. Especially concerning the AI-features, discovering how they should be designed is crucial. Papers on the uncertainties of AI-features are emerging in abundance. For example, Zhan et al's (2023) paper found that according to recent studies, 40% of people in the U.S. fear AI in some form, from privacy issues to lessened autonomy and fear of replacement. Identifying how to implement the AI-features so that the users embrace them is crucial to Sievo's product's success.

The research will be done by identifying data analytics users' current challenges, as well as discovering how they think and hope data analytics will change in the future. Then, this thesis will explore which features and technologies Sievo should focus on going forward, and what to take into account in their design to achieve the best outcome.

1.2 Research problem and questions

The research problem is at the root of the research for this thesis. It is supported by three research questions, the results of which form the answer to the overarching research problem.

With the first research question, the thesis aims to gain an understanding of procurement software users' current state. After the now is understood, the second research question will gauge out what technologies and features will be important to the users in the future. Finally, the third research question discusses how the technologies and features found in the previous research question should be designed to achieve the best user experience.

Research problem: What design guidelines are important for future procurement analytics software?

RQ1 : What are the users' current challenges in data analytics software?

RQ2: Which new technologies and features will be important to procurement users in the future?

RQ3: What design principles should be adopted to maximize the user experience of the new technologies and features?

1.3 Scope of the thesis

This thesis focuses on the users' side of things, and consequently will not delve deep into the technical implementation challenges and solutions of analytics software. The thesis will retain the point of view of a service designer, not a data engineer or a system architect. While factors like data quality are important and, when poorly implemented, will negatively affect the user experience, it is not in the scope of this thesis to examine how to properly handle large amounts of complex data in the integration process. In addition, the thesis is focusing on the future technologies and futures, and thus will not much discuss how to improve the existing product features.

Table 1 illustrates how the research questions are going to be answered. A capital "X" indicates that most of the answer to the research question will emerge from the corresponding section (literature review or empirical study), while a small "x" indicates that a lesser part of the answer comes from the related section.

	Literature review	Empirical study
RQ1	X	x
RQ2	x	X
RQ3	X	X

Table 1: Distribution of research

1.4 Structure of the thesis

This thesis starts with an introduction, setting the stage, context and motivation for the work. Chapter 2 describes the research methods used to probe answers to the research problem and questions, in this case a literature review and interviews.

Chapter 3 presents the results of the literature review, presenting answers to research questions 1-3 in their own subchapters. Chapter 4 is laid out in a similar manner, but presents the results of the empirical study, i.e. the interviews and gives voice to Sievo's customers and employees.

After the results are presented, chapter 5 discusses the findings of both the literature review and the interviews, and makes comparisons between the findings of the two methods. Finally, chapter 6 draws conclusions from the most important results.

2 Research methods

2.0.1 Overview of the research process and methods

Due to the scope and restrictions of the thesis, the research process followed qualitative measures. Literature presents a wide plethora of varying recommendations and guidelines on how to execute qualitative research. Hossain (2011) found in their research a general skeleton for qualitative research, which was used as a base for the research process in this thesis. Despite it being almost fifteen years old, Hossain's (2011) bears much resemblance to newer propositions. One example of such new propositions is the one put forth by Nichols (2023), who leans their proposed research process into a framework presented by Nielsen and Norman group. However, Hossain's (2011) process description was presented much simpler than most of the newer ones, which is why it was chosen to serve as a base for this research.

In Figure 1 below is depicted the qualitative reserach process discussed by Hossain (2011). Overall, the process consists of research problem identification, a literature review, preparing for the empirical part, executing the empiric research, analyzing the acquired data and reporting results. The yellow tickets represent the process as illustrated by Hossain (2011), with the added step of preparing for the interviews. The green tickets on the right depict the main activities to support the yellow step, and they are there to provide a bit more fleshed out depiction of the process.

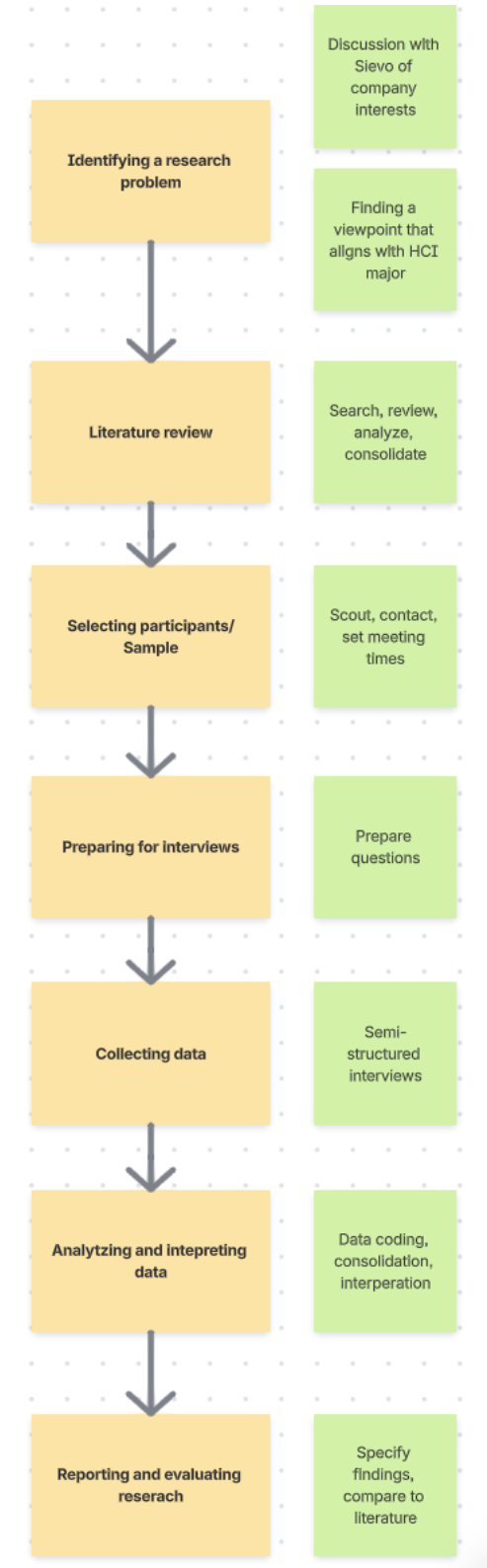

Figure 1: Research process diagram

2.1 Literature review

Literature search

The literature used in this thesis was searched for mainly through Google Scholar to heighten the academic viability of the papers. Some resources were found through a "normal" Google search.

Literature was searched for based on the research questions. The research questions were used as starting points for the literature search, and when a few papers were found, the themes in those papers led to diving deeper into the emerging topics. For example, the answer to research question one "What are the users' current challenges in data analytics solutions?" consists of multiple factors, including (but not limited to) information visualization and the need for personalization. Some of these factors were known parts of the issue beforehand by Sievo's design team based on user feedback, while other factors arose from the literature review process. These factors are specific enough to yield relevant literature, and the combination of them formed the literary answer to each research question.

Literature selection

The selection of the literature was based on how well each paper provided an answer to a research question, as well as academic viability. In any case, the academic viability of sources had to be confirmed by inspecting the writer(s) and the publisher. Academically accomplished people, reputable universities and renowned conferences of relevant fields were considered viable sources. Other important metrics for selection were scope, relationship to other works, study methodology, and publication date. When selecting the papers to be used, ones with promising titles and abstracts were considered for further inspection, and a brief reading revealed whether the content was truly relevant.

Literature analysis

The analysis of a paper began first reading the entire paper. Then, the paper was read again, this time taking notes of the relevant insights related to the research question in processing. When a few papers on a given subject had gone through this process, the insights were combined into a table that showed who was the source for which insight. The table enabled spotting repeated themes and differing opinions at a glance, which formed a clear picture of the central themes of the upcoming writing. If some insights in the table were not clear enough, the researcher went back to read the portion of the paper discussing it so full context could be understood.

2.2 Empirical study

2.2.1 Case description: the Sievo Vision project & Prototype

Sievo's product is constantly looking to differentiate against both competitor products and do-it-yourself solutions, such as Microsoft's PowerBI. The Product Management function and the Service Design team at Sievo have been looking into how to stay ahead of the competition in a project called Sievo Vision. In 2024, the design team ran internal interviews within Sievo. The purpose of these interviews was to gain an understanding of what works well in Sievo, what challenges users have, ask about visions for an 'ideal' state of what the ultimate procurement tool could be, and finally, what themes the interviewees hold important regarding future development. These internal interviews were held in order to gain an understanding of Sievo's possible direction of development for the future, which then would be taken to customers at a later phase to be validated and challenged.

Based on theses interviews' results, a few key themes were indeed recognized and built into a high level product prototype in Figma, a user interface design tool. The purpose of the prototype was to combine the most relevant themes found in the previous round of interviews and to concretize them. The prototype was developed by two of Sievo's senior service designers. I was involved only when it became apparent that I would be writing my thesis on a subject closely related to the Vision project and that the prototype would be used in my interviews. By the time I was included in the prototype's construction, it was almost ready, and I contributed only to a few refinement adjustments. The prototype constructed a narrative of two people working in Sievo, showcasing the core themes and features that came up in the internal interviews. The nine core themes were:

1. **Connectivity** - Sievo being connected to external systems, such as Microsoft Teams or Slack.

2. **Personalization** - The content a user sees would vary depending on their role and responsibilities, highlighting what's most relevant to them.

3. **Collaboration** - Users would be able to collaborate with their colleagues effortlessly, for example by sending each other messages within Sievo.

4. **AI-assisted work** - An AI agent would be available to help the users to gain information and take action

5. **Guiding insights** - Sievo would provide intelligent insights so that the user wouldn't have to dig them up from the dashboards themselves. What's more, Sievo could suggest action pointers to the user and help them take initiative.

6. **Community benchmarking** - Sievo would, with the permission of it's users, feature a community data hub where users could see how they position on payment terms and other metrics in relation to other Sievo clients. This would allow for benchmarking and help with the users' decision making.

7. **Actions Initiated from Sievo** - Sievo could prompt the user to take action, and act as a starting point for taking action. Users could create initiatives, launch supplier negotiations and more directly from Sievo.

8. **Finance view** - A tool visualizing monetary effects of initiatives and actions, to help the finance function to inspect and validate the decisions of the procurement department, ensuring mutual agreement and speaking the same language

9. **Saving realized** - After the user has taken action, it would be reflected in their own Sievo, showcasing the status of the initiative and any savings or other benefits achieved.

The prototype was a narrative one, following made up users' workflow with Sievo and illustrating conceptual ideas of features that Sievo could have in the future. The prototype bore similarities to what Sievo looks like in color and general layout, but kept the features shown very high-level in order to help the viewer focus on the ideas represented as opposed to details in the user interface. Figure 2 below shows an illustration of the layout showcasing the AI insights part. The UI is stripped of all unnecessary content to let the viewer focus on the intended feature. In addition, there is a text box summarizing this part of the story, which corresponds to the service designer presenting the proto and narrating the story. The prototype was presented in the interviews to the interviewee, and the viewer did not interact with it directly.

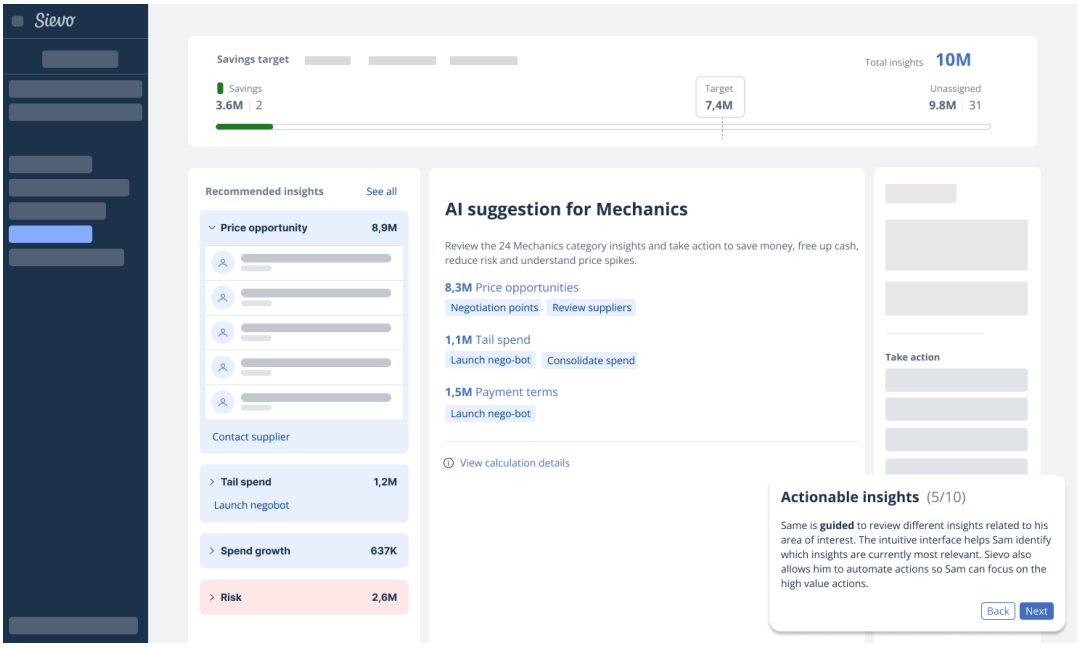

Figure 2: A part of the prototype, showcasing the AI insights

2.2.2 Research process

Research method: the semi-structured interview

The goal of the interviews was to

1. Gain a better understanding of Sievo users' current state in the context of their work
2. Validate whether the prototype illustrating the possible future direction of Sievo is desirable for the customers
3. Probe for any new insights concerning the future direction of procurement work and Sievo.

The interviews were held as semi-structured interviews. This approach was chosen to derive the information desired while still allowing for rather free discussion and spontaneous insights. As the number of sessions was relatively small, ten or less, it was preferable to opt for qualitative data collection and analysis. DiCicco-Bloom and Crabtree (2006) note that structured interviews tend to yield quantitative data, so semi-structured or unstructured interviews are better for qualitative data collection and analysis. Completely unstructured interviews were not suitable either, as the interviews were on a quite tight schedule and had a clear purpose on what information was to be derived. Omitting the structured and unstructured interviews leaves the semi-structured interview.

As DiCicco-Bloom and Crabtree (2006) state, the semi-structured interview is iterative in nature, which means that each session is different. The format allows for the discussion to dive deeper into whatever the interviewee is most interested in or has the most knowledge about. This is advantageous, as if different interviewees highlight the same topics, they can be validated as important to most. Then again, if the interviewees raise very different topics, further investigation is needed to deduce where the discrepancies arise: different needs of the users, poorly constructed interview questions or simply abundant offering of important features, or a combination of the aforementioned.

The customer interviews and Sievo's top management interviews were conducted as individual interviews, while the rest of the internal interviews were conducted as a joint session of two interviewees per function. Individual interviews allow for going deeper into an individual's interests, while group interviews gets a wider range of experience faster (DiCicco-Bloom and Crabtree, 2006). Because there were a total of ten people to interview internally, group interviews made the process a lot quicker. However, because in a group dynamics affect the outcome, I as the conductor had to be mindful of said dynamics as DiCicco-Bloom and Crabtree (2006) recommend. For example, if one of the interviewees was a more powerful presence than the other, I had to be more proactive with the quieter one to make sure their insights were included as well. This is also the reason why the CEO of Sievo and the vice president of product management were interviewed individually, to avoid positions of authority influencing the sessions. The internal interviewees were picked so that they knew each other

beforehand and were of equal titles, so that the situation would be as comfortable as possible and one interviewee would not shy away from the other.

Considering other methods of data collection, there are, for example, observations. Observations were not a viable option due to the time constraint of the project and this thesis. In the case of Sievo customers, arranging a visit to their offices and spending time there would have essentially ruled all non-Finnish customers out for monetary reasons. Even with Finnish customers, arranging visits and observing Sievo users would have taken months, realistically speaking. If it had been possible, observing the users could have been highly beneficial, as it would have given insight to how the users actually use Sievo in the context of their work. It would also have served to gain a better understanding of procurement work at large and potentially revealed some opportunities for development. However, large-scale observations are impossible to execute with small resources and time, and a small pool of customers would not adequately represent Sievo's nearly 200 customer companies and their wide range of end users.

Questionnaires could have been used to complement the interviews or get responses from clients that couldn't participate in an interview. However, they were ruled out as they do not allow for the desired deep insights nor spontaneous discussion. Moreover, one of the goals of the interviews was to validate the vision prototype, and a questionnaire wouldn't have been able to effectively leverage it.

The interviewees

For this thesis, there are two main groups of interviewees:

- Sievo customer users
- Sievo employees

Within the Sievo customer users, requirements were simple. They had to be people familiar with Sievo as a product, preferably working in a procurement function but this was not mandatory. Customers were contacted following Sievo's guidelines. Right now, the design team at Sievo doesn't have the permissions to directly contact customers on their own. Instead, I first contacted the Customer Success function in their Slack channel, introducing the topic and asking if anyone knew customers who might have willing participants. A few customer success managers (CSMs) and key account managers (KAMs) answered this message, offering eight customers in total. The CSMs and KAMs wanted to give their customers heads-ups in their weekly meetings before any emails were sent. After a few weeks of waiting, two customers had been taken off the table, but the rest were willing to participate. After the CSMs and KAMs had greenlit the customers, I sent them all emails regarding the interviews, explaining the agenda and suggesting several timeslots for the meetings. In the end I got only three replies to my emails. One customer suggested meeting much later, outside of the timeframe the interviews have to be done regarding this thesis. So, I got two customer interviews done.

Because the pool of customers interviewed did not suffice for our research in the design team nor this thesis, I had to complement them with internal interviews within Sievo. I interviewed five functions within Sievo employees:

- The design team
- Product Management
- Sales
- Customer Success
- Visionaries (management)

These groups were chosen based on their potential knowledge regarding the goal of the interviews. Each of these roles have a different viewpoint on the topic, which, as recommended by DiCicco-Bloom and Crabtree (2006), maximizes the depth and richness of the gained insights while maintaining a group that has shared experiences of the topics.

The design team is very familiar with Sievo as a product, being responsible for designing the user interfaces. Their work requires lots of customer research and thus provides them with a rich understanding of user issues, needs and hopes.

Product managers work closely with the designers. They are responsible for the strategic direction of their assigned product area, i.e. what is developed and when. They too have to have an understanding of user needs, issues and wishes in order to oversee that the right product is being developed.

Sales is responsible for selling the product to potential Sievo customers, both for prospects and upsales for existing customers. Thus, sales have a good understanding of what users want and which factors tip them over the edge when deciding on purchasing Sievo.

Customer success works directly with the customers as well, acting as constant support and a first point of contact in case of any issues. As such, they know Sievo customers well and can provide valuable insights into their current issues and improvement wishes.

Lastly, the visionaries: these people were plucked from the management team: the CEO of Sievo as well as the vice president of product management. These people are the driving force behind Sievo's products' strategic direction. They engage actively with prospects, customers and Sievo employees, and try to derive the best initiatives for Sievo to undertake in order to stay ahead of the competition and deliver the best possible product to its customers.

The designers, product managers and visionaries were chosen directly. The design team is rather small, so the two that were not involved in the vision project earlier

were chosen to minimize bias. Out of product managers, two were chosen that were responsible for big, important customer facing products. Lastly, visionaries were chosen out of the management team referencing their relevance to this project. Sales and customer success functions were contacted on their respective Slack channels, out of which volunteers emerged.

Table 2: Summary of interviewees

	Customer or Sievo & Function	**Title**	**Years in role**	**Main responsibilities**
1	**Customer /** Analytics, procurement	Analyst and Insights partner	10	deriving analytics and insights, change management, process streamlining
2	**Customer /** Management and operations	Operations manager	5	providing tools and data to supply chain responsibles
3	Sievo / Product Management	Product manager	1	Leading the development of a product, ownership and strategy of said product. Collaboration with relevant stakeholders
4	Sievo / Product Management	Product manager	1	Leading the development of a product, ownership and strategy of said product. Collaboration with relevant stakeholders
5	Sievo / Product Management, Service Design	Senior service designer	5	product development, user research, UI and UX design
6	Sievo / Product Management, Service Design	Service designer	5	product development, user research, UI and UX design
7	Sievo / Product Management	Vice President of product management	2	Leading the product management function, head of product strategy, vision and direction
8	Sievo / Management	CEO of Sievo Oy	20	Discuss with customers and prospects, lead the management team and Sievo as a whole, understand the wider procurement and software space

	Customer or Sievo & Function	Title	Years in role	Main responsibilities
9	Sievo / Sales	Partnerships manager	5	manage consulting partnerships
10	Sievo/ Sales	Head of European sales	11	ensure that leads convert into sales, team management and support
11	Sievo / Customer Success	Account director	9	planning with customers, upsales, contracts, firefighting, team support
12	Sievo / Customer Success	Vice President of Value Enablement team	4	Lead the strategy and direction of the value enablement function. Team and process development, skill management, pricing, marketing, firefighting

Interview structure & questions

The interview questions were constructed together with two other senior designers, who have been involved in the Sievo Vision project for a longer time. Because these customer interviews were conducted for the Vision project first, and my thesis second, I was not able to fully decide the questions asked, especially in the customer interviews. Lastly, the interview session leveraged the Figma prototype, described in the previous section that showcased Sievo's initial vision of the product's future features.

The interviews followed the same core structure, but the specific questions varied a bit per interviewee group. Sievo employees couldn't answer questions that were formed to derive opinions directly from customers, so their questions had to have more of a speculative nature or lean on their experiences. Furthermore, some questions were removed or added considering the viewpoint the interviewee had and the nature of the input they could provide. For example, interviewees from the sales function don't know much about where the users struggle when actually using Sievo, but they know what impresses prospects in sales processes and what issues customers are trying to solve with Sievo. In some interviews, spontaneous questions emerged when the interviewee said something interesting that required further elaboration. Lastly, the topics discussed varied in order depending on the flow of the conversation.

Introductions. The sessions began by establishing rapport, as recommended by DiCicco-Bloom and Crabtree (2006). Before any official agenda began, there was a moment reserved for casual chit-chat, the how are you's, and a round of introductions. Casual conversation eased the interviewee into the situation so that they didn't not feel too formal or threatened. Once everyone was settled, the intervie-

wee was reminded of the purpose of the interview (thesis and the vision project) as well as asked to consent to being recorded and to their insights being used anonymously.

Current situation. The agenda got started with some introductory questions about the interviewee and their current situation. These questions were open-ended, keeping the tone of the interviewee neutral and non-guiding. The purpose of these questions is to understand the customer's context.

Future vision. After understanding the current situation, the interviewee was asked to think about their vision for the future of procurement work. One of the goals of the session was to validate Sievo's vision of the future of procurement work (realized in the prototype) but we wanted to first hear of the interviewee's vision without any guidance from us. Of course, in the case of Sievo employees they already have some idea on the future initiatives of the company, but also have different viewpoints on the topic.

Prototype walkthrough. After establishing the interviewee's future vision, it was time to present Sievo's vision. This vision was represented by the prototype in Figma that shows how Sievo could work in the future. The interviewee is walked through the prototype, and they are free to interrupt and ask questions during the walkthrough. The prototype follows a few imaginary users' workflows within Sievo and constructs a coherent narrative. Most importantly, it highlights the nine central themes introduced earlier when discussing the empirical research methods and the Sievo Vision prototype.

Prototype feedback and discussion. After the entire prototype was shown, the interviewee was inquired about their initial feelings, after which they were asked to choose the most important or interesting themes for them. In this stage, the interviewee was shown a Miro board with screenshots of the prototype and short notes of each theme to help better remember them. After the most important themes were chosen, the interviewees were inquired in-depth about the chosen themes. If there was time to spare, the other, not-most-important-themes were discussed as well.

Closing and thank you's. When there was approximately five minutes of the meeting left, deeper discussions had to be cut and the interviewee was thanked for their time and asked if they had any questions for the interviewer. Then, the interviews were closed.

2.2.3 Data collection and analysis

The data for this thesis' empirical part was collected from the interviews. The interviews were held live whenever possible, but remote meetings were used for situations when all parties could not make it to the same location. In both situations, the sessions were recorded with Microsoft Teams. The recording included both audio and video of the session. Teams' built-in transcriber was used to initially transcribe the meeting. The transcribes had to be edited manually after the meetings, as the automatic

transcriber made many mistakes and misinterpretations. As DiCicco-Bloom and Crabtree (2006) discuss, an automatic transcriber struggles to sometimes differentiate words and constructs sentences wrong, skewing their meaning. Thus, the automatic transcription served as a base for the transcriptions, but they had to be edited to be accurate.

Data analysis happened concurrently with and after the data collection, i.e., the interviews. The approach used to analyze the data was a modified version of a code-based approach. De Casterlé et al. (2012) argue that researchers have become over-reliant on qualitative software such as Atlas.ti, which leads to neglecting the actual reading and reflection of the material. They suggest a very thorough, 10-stage analysis, which was adopted to a degree. First, as per de Casterlé et al. (2012), the interviews were read through to form a coherent picture of them. Then, the research questions were used as the concepts introduced by de Casterlé et al. (2012) with which the transcripts were coded. The coding happened with color labels in Google Docs, each label corresponding to a research question. The interviews were coded research question by research question, so each was read four times in total. The steps after the coding differed from de Casterlé et al's (2012) suggestion. While analyzing codes in a software like Atlas.ti is a popular approach, I've found it difficult to maintain an overview of the results and have the insights nicely grouped so that the writing process would be fluent. So, after the key points of each interview for the research question were marked on the transcription, the collective findings were gathered on a board in Confluence, which is a documentation tool. Each interview was given their own color, so it was easy to differentiate who said what. The findings were then grouped by emerged themes, which then were written open in the results section. This process was repeated for each research question.

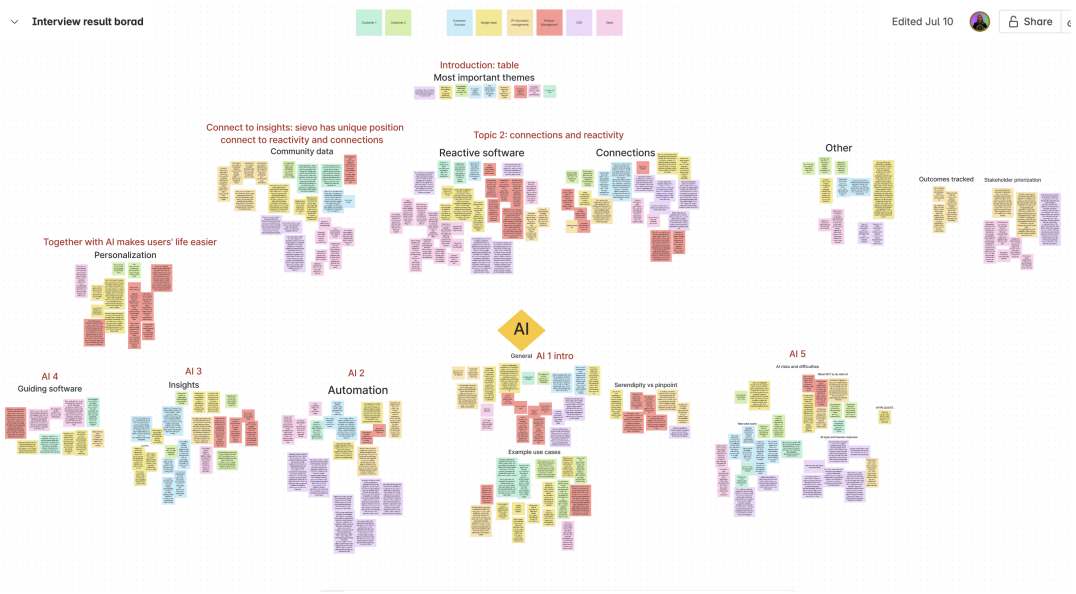

Figure 3: Confluence board of interview data of research question 2

Figure 4: Confluence board detail of insights on AI-related risks

The ethical side of the the interviews was covered as well. DiCicco-Bloom and Crabtree (2006) demand that interviewees are sufficiently informed on the purpose of the interview and how their personal information is handled. The interviewees were informed on the dual purpose of the session (thesis and the vision project) both on the initial contact message and in the start of the actual session. Before the session moved on to the agenda and recording started, the participants were separately asked if they consent to be recorded and their insights to be used in the vision project and this thesis. The recording and agenda started only when this consent was achieved. The participants were promised anonymity, and the meeting recordings were promised to be destroyed once the thesis was completed, but by September 1st, 2025 the latest in any case.

3 Results of the literature review

3.1 Introduction to data and procurement analytics

Defining data analytics

In today's increasingly digitalized world, data is generated faster than ever. The amount of data is reaching record highs each year and the amount is forecasted to only continue growing (Statistia, 2024). Due to the explosive pace and volume with which data is being generated, humans cannot leverage the insights hidden in the data without utilizing data analytics.

Vassakis, et al. (2018) define data analytics as managing and analyzing large amounts of data. Managing refers to the acquisition, extraction and integration of data, whereas the analyzing refers to the process of transforming the data and presenting it in a decipherable way, such as with dashboards. Hariri, et al. (2019) present a similar definition: the process of analyzing massive datasets to derive value from the data, such as market trends or users' behavioral patterns. Zhou et al. (2014) do not outright define data analytics, but refer to it as a means to exploit data. Stieglitz et al. (2018) define analytics as the discovery, collection, preparation and analysis of data.

Following these definitions we can define data analytics as follows: **the process of acquiring, integrating and analyzing large amounts of data with the goal of deriving value from it.**

Data analytics can be divided into further subcategories. Shao et al. (2022) divides into five "levels", depicted in Figure 5: data collection, descriptive analytics, predictive analytics, prescriptive analytics and cognitive analytics. Data collection is not analytics, but it is included as a prerequisite for analytics, for without sound data collection, analysis cannot be done. Descriptive analytics refer to analytics that describe or visualize the data, but leave the interpretation to the viewer. Predictive analytics include analyzing old data and making predictions of future trends based on it. Prescriptive analytics build on predictive by adding a layer of speculated actions and their possible outcomes, helping the users in operative decision making. Lastly, there is cognitive analytics that leverages advanced technology, such as machine learning and artificial intelligence to optimize processes and reduce human labor. (Shao et al., 2022).

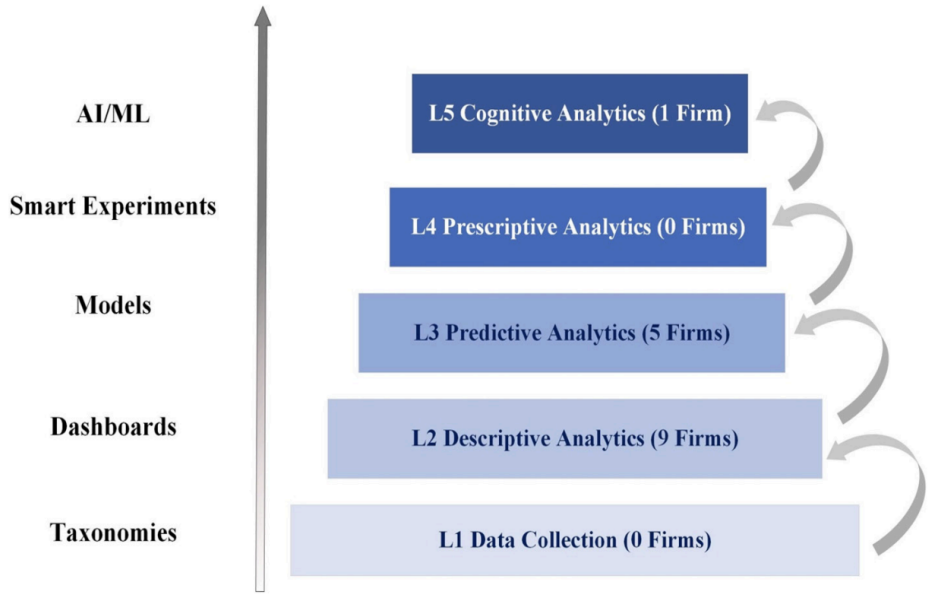

Figure 5: Data analytics hierarchy by Shao et al. (2022)

Vassakis et al. (2018) make a different division of analytics. They divide data analytics into two: conventional and big data analytics. The conventional analytics includes Shao et al.'s (2022) three lowest levels: data collection, descriptive and predictive analytics. The big data analytics on the other hand, includes Shao et al.'s (2022) top two levels of data analytics: prescriptive and cognitive. A key difference in the two papers' definitions is that Shao et al. (2022) assume that even the low-level descriptive analytics operate in real time, while Vassakis et al. (2018) describe it as leaning onto static pools of data, coming in at regular intervals daily or so.

Considering Sievo, it has previously sat firmly within descriptive analytics, and does not feature any real-time data. However, the company is now looking into moving up the hierarchy, and has already included predictive and early cognitive analytics in its product. Though prescriptive analytics is lower on the hierarchy than cognitive analytics, it represents a horizontal kind of shift for Sievo, rather than vertical. Sievo has been a strategic tool for large enterprises, and as such has not featured operational analytics. The company is looking into integrating predictive analytics and cognitive analytics into its strategic features, before considering including operative, prescriptive analytics.

There are many advantages to using data analytics. Vassakis, et al. (2018); Hariri et al. (2018); Zhou et al. (2014); Garoufallou & Gaitanou (2021); Shao et al. (2022), Stieglitz (2018) as well as Khalifa (2019) all mention numerous advantages to using data analytics. Table 3 (below) illustrates these benefits and which sources mentioned which advantages.

Table 3: Advantages of data analytics

Advantage / Source	Improved decision making	Enables data-driven innovation and discovery	Reduces risk in decision making	Helps to improve existing services	Helps to provide a personalized experience	Cost reduction and driving economic value
Garoufallou & Gaitanou (2021)	X	X		X	X	
Shao et al (2022)	X	X	X	X		X
Stieglitz et al. (2018)	X					
Hariri et al. (2019)	X		X	X		
Khalifa (2019)	X			X		X
Vassakis et al. (2018)	X	X		X		X
Zhou et al. (2014)	X	X		X	X	X

From Table 3 we can see that the main benefit of data analytics is improved decision making. Data analytics helps professionals' decision making by reducing human bias, reinforcing existing knowledge and revealing new insights that would have been otherwise lost in the data. In addition, data analytics can enable data-driven innovation of new services or opportunities (Vassakis et al., 2018; Garoufallou & Gaitanou), or even scientific disocvery (Khalifa, 2019).

Defining procurement analytics

As this thesis focuses in procurement analytics, there is reason to clearly to define the term "procurement". Mak (2014) in their research does an extensive review of the word through linguistics, evolution from its militaristic origin and modern use. In the end, they come up with the following definition:

"*A careful, usually documented process resulting in delivery of goods or services to be delivered within a set time period.*" (Mak, 2014: 13).

Although they did find a definition, Mak (2014) recognizes that there is room for future research. In the context of this thesis, we will consider procurement in the context of business use. Atabayeva (2022) defines procurement as

"*timely, efficient and complete provision of activities with goods, works and services with the required price and quality indicators and their favorable conditions for the acquisition, taking into account the specifics of the organization of economic activities and the fulfillment of legislative requirements*" (Atabayeva, 2022: 1).

Ultimately, they state that procurement activities' goal is to create the best condition for the purchase of goods and services. This definition aligns with Mak's (2014) and provides it in more detail and in the context that this thesis if focusing on.

It is important to note the difference between procurement and purchasing: purchasing is a part of procurement. A non-procurement expert can purchase a sofa with a single phone call, without considering competition or the sustainability of their choice. As such, purchasing as a process can be very simple. However, procurement professionals aim to make the best attainments following varying heuristics and complicated processes. (Mak, 2014).

According to Mak (2014) as well as Atabayeva (2022) and Easton et al. (2019) procurement activities include, but are not limited to:

- supplier benchmarking
- supplier negotiations
- contract management and supplier selection
- supplier relationship management
- company spend tracking
- savings opportunity monitoring
- material cost budgeting and forecasting

Procurement activities are many and varied. As such, as Shao et al. (2022) note, there are ample opportunities to take advantage of analytics. The field employs the same strategies of data-driven, advanced analytics-based decision making to unlock business insights, optimize processes and managing the supply chain as other fields of analytics (Sievo Oy, 2024). As Shao et al. (2022) describe, procurement is a vital support function because every company has to purchase things in order to produce goods or services. Purchasing leaves a trail of actions and costs, from emails, receipts, contracts, which form the very data that procurement professionals use. Large, multi-million enterprises have so much of this data, that they must employ analytics to manage their spending more effectively (Shao et al., 2022) .

As procurement analytics is a narrow field, searching for literature on challenges of procurement users did not yield usable results. The literature was searched for concerning data analytics users, but since procurement analytics is a subset of data analytics, this is a viable approach.

3.2 Users' current challenges in data analytics software

While data analytics has become an essential tool for many, it does not come without issues. Table 4 below summarizes the challenges faced by data analytics users, as found in the literature review.

Source Challenge	Garoufallou & Gaitanou (2021)	Shao et al (2022)	Stieglitz et al. (2018)	Hariri et al. (2019)	Khalifa (2019)	Vassakis et al. (2018)	Zhou et al. (2014)
Need for advanced analytics techniques	X	X	X	X	X	X	X
Low data quality	X	X	X	X	X	X	X
Data security and privacy issues	X					X	X
Velocity of data generation	X		X		X	X	
Visualizing what's relevant	X	X	X			X	
Increased need for data professionals	X	X	X		X	X	X
High learning curve	X	X			X		
Attitudes towards new technology and processes	X	X	X		X	X	X
Gaps between leadership, data experts and end users	X	X	X		X	X	
Wrong or uncontextualised insights	X			X			

Table 4: Challenges of data analytics

As Table 4 illustrates, there are many challenges that may arise when using data analytics software. Keeping in mind the scope of this thesis, it is not relevant to analyze in-depth the issues that relate to technical implementation or client-side strategic issues. These issues are:

- The need for advanced analytics techniques
- Low data quality
- Increased costs
- Data security
- Velocity of data generation

The **need for advanced data analytics** techniques arises from the volume, variance, quality and velocity of the data generated. Companies have to leverage advanced methods, such as specialized software like Sievo or SAP, machine learning and artificial intelligence. (Garoufallou & Gaitanou, 2021; Hariri et al. , 2019; Vassakis et al., 2019; Zhou et al., 2014).

High volumes of varied data also easily leads to **poor data quality**, which then has to undergo more processing before it can be used for analysis (Zhou et al, 2014).

Increased costs are a consequence of having to use such advanced processing techniques in order to handle the high volumes of rapidly generated, varied data (Shao et al., 2022; Khalifa, 2019; Zhou et al., 2014).

Lastly, **data security** is an ever-present issue. Zhou et al. (2014) notes that with increasingly complex data processing processes, the possibility for a weak link in the data pipeline increases, and that a breach at any state can lead to problems of great magnitude.

These aforementioned issues could be addressed, to a degree, by the analytics software provider, and the end result would likely enhance the overall user experience. However, the issues cannot be resolved by service design of the analytics software provider. The issues are related to the technical design and implementation, which is out of the scope of this thesis. Consequently, they will not be discussed in-depth. Next, the issues that **can** be addressed by the analytics software's service design will be analyzed.

3.2.1 Visualizing what's relevant

When data is plentiful and it's being processed with highly advanced techniques, a new problem arises: there's too much potential insights to interpret. It becomes increasingly difficult to extract the meaningful insights and prioritize them for the

users. A high-dimensional decision space has no uniform design, and there can be an overwhelming amount of potentially interesting insights and the user no longer knows what they should focus on (Zhou et al., 2014; Stieglitz et al., 2018). Zhou et al. (2014) notes that different users have different interests from the data, which further highlights the problem of how to prioritize the findings in the user interface. Shao et al. (2022) note that analytics tools tend to not be very user friendly, and the sheer amount of data and insight priorization issues are a likely part of the problem. When the software is difficult to use, the users then have to spend time learning the software and the data, because the descriptive analytics doesn't effectively tell them what is most valuable for them. Lastly Zhou et al. (2014) mentions that changes made to the design of an analytics application can be expensive, leading to rigid software that is slow to response to user needs.

Although data is plentiful, one special type of data actually seems to be largely missing from the analytics solutions: real-time data. Users often need to take crucial action based on real time data, for example in healthcare (Khalifa, 2019). However, analytics software can be ill-suited for quick decision making (Stieglitz et al., 2018). The aforementioned rigidness of analytics software and the difficulty of prioritization of insights are likely factors in this matter. The reason for the lack of real-time data seems to be mainly technical. Because of the volume of data, in order to generate insights in a timely manner, high levels of optimization are needed (Zhou et al. 2014) which are then more vulnerable to mistakes (Hariri et al. , 2019; Zhou et al., 2014). In addition, high levels of rapid optimization require advanced methods like machine learning and artificial intelligence, again adding to the cost and talent required.

3.2.2 Increased need for data professionals

As a company increasingly leverages data in its operations, they then have to find more talent with the required technical skills who can extract, transform, visualize and analyze the data (Garoufallou & Gaitanou, 2021; Vassakis et al., 2018). These skills can be sparse and expensive to acquire, and even when hired, they require training and time before they start to produce value (Shao et al., 2022). However, if these skills are not present, it can lead to poor handling of the data, which can ultimately result in false insights and discoveries (Zhou et al., 2014).

One of the major factors contributing to the increased need for data professionals is the high learning curve of data analytics software, which is a topic big enough that it warrants its own subchapter of discussion.

3.2.3 High learning curve

Even non-technical experts have to brush up their skills to be able to use the analytics in their work (Garoufallou & Gaitanou, 2021; Khalifa, 2019; Shao et al., 2022). This might entail familiarizing with a new software, learning how to read data charts, learning to deduce what is relevant information and what is redundant, and more. Ali et

al. (2016) notes that oftentimes, new systems require new IT skills which the employees might lack This leads to users having to pour significant amounts of time into learning the new system, which reduces their overall work efficiency and can lead to frustration (Ali et al., 2016). The findings of Ali et al. (2016) reinforce the issue of a high learning curve in data analytics solutions presented by Garoufallou & Gaitanou (2021), Khalifa (2019) and Shao et al. (2022). In addition, Rafique et al. (2012) notes that system learnability, while a crucial factor to overall usability, seems to be often overlooked.

Laumer & Eckhardt (2012) underline the importance of first impressions and easy learnability in software: they note that users likely review a system against the potential inputs and outputs it would have on their work. If this evaluation results in a net negative result, they are likely to reject the system. Rafique et al. (2012) likewise states that good learnability is vital to he initial rejection or acceptance of a system. Rafique et al. (2012) and Kendrick (2019) both conclude that good learnability keeps the time spent to learn a system moderate, thus lowering training costs and resulting in an overall better user satisfaction. They both state that with good learnability the users' productivity is better during the learning process, which, as Kendrick (2019) states, helps to empower the users; they feel competent at their work.

Kendrick (2019) presents three degrees of system learnability, which are depicted below in Table 5. The three degrees of learnability in a given system are first-use learnability, steepness of the learning curve and the ultimate plateau of use. Each of the three degrees can be evaluated by the metrics described in the table, and the optimal users refer to users to whom the corresponding degree is the most important. For example, high first-use learnability would be more important to users who seldom visit the system over users who use it in their daily work. (Kendrick, 2019).

Degree of learnability	First-use learnability	Steepness of the learning curve	The ultimate plateau
Evaluation metric	How easy is the system to use for first-time users?	How quickly will the users get better with repeated use of the system?	How efficient are users in their work when they use the system in the most optimal way?
Optimal users	Users who visit the system or task only once	Users who will use the system multiple times, but not excessively	Expert users who depend on the system in their daily work

Table 5: Degrees of learnability by Kendrick et al. (2019)

Kendrick et al. (2019) notes that because of the differing degree to which users use

a system, they have different acceptance levels for learning a system, and the software providers often have to make compromises on the designs and prioritize the users that have the highest business value. In an expert procurement software like Sievo, one could consider the users from a business perspective as follows: customer prospects have to be convinced with high first-use learnability in order to make a sale, while for customer retention, a manageable learning curve and a high ultimate plateau become much more important.

3.2.4 Attitudes towards new technology and processes

Adoption of new software is not purely dependent on the ease of learning of a given tool. The data and technology landscape is evolving rapidly, and with every new tool or process that a company adopts, its employees have to adapt. In essence, people have to be able to adapt to a frequent cycle of changes in their working tools and processes, which can be difficult for a number of reasons. While the deep psychological explanations of resistance to change and the organizational strategies to manage change are not in the scope of this thesis, it is relevant to understand the fundamental factors of the issue. When a company adopts a new software such as Sievo, there are things the software provider can do to make the adoption of the system easier on the client company and the end users. Easier adoption likely leads to greater user satisfaction, which in turn leads to greater customer retention, yielding value to both the customer and the service provider.

Introducing new software is a form of introducing change in people's work. In their paper, Burnes (2015) conducts an extensive literature review on understanding resistance to change. They present that some sources tend to underline individuals' resistance to change, while others focus on organizational difficulties with change. In the end, they present four theories that are major factors in people's resistance to change:

- **Cognitive Dissonance** - inconsistencies or mutually exclusive goals within people's work or company make people uncomfortable.
- **Depth of Intervention** - when employees are involved in the change process, they feel a sense of control and respond better during and after the implemented change
- **Psychological contract** - there is an unwritten set of expectations regarding a person's responsibilities, compensation, working hours, company hierarchy and so forth. Violations of this set of unspoken rules can lead to unrest and even conflict.
- **Dispositional resistance** - individuals differ on the degree on which they are disposed to accept or resist change. Acknowledging this helps to manage people during change processes.

Now that we understand the fundamental psychological factors that apply to introducing any change, let's further inspect introducing new technology and its challenges. The obvious, intuitive answer to "Why people don't like new technology" is that the service or product in question does not cater to the users' needs, or the users perceive that it does not do so. There might be a few reasons why this might happen, which are discussed below in more detail.

Khalifa (2019) and Shao et al., (2022) bring forth negative attitudes towards new technology and analytics, as well as adopting new practices related to them. They explain that highly trained professionals are used to relying on their own expertise and are naturally vary of a computer handling critical decision-making information. Though, in medical analytics, which is what Khalifa (2019) researched, professionals may be more sensitive to relying on technology with people's lives at stake than people working in technology or commerce, where any potential damage is mostly monetary. Shao et al. (2022) note that the problem is often in the organization culture and getting people to understand the value of data.

Ali et al. (2016) conducted a literature review on user resistance in information technology (IT). They identified a wide plethora of causes for IT resistance, and divided them into three categories: people oriented, system oriented and interaction oriented. Table 6 depicts the causes put forth by Ali et al. (2016) with some modifications: system reliability and data quality issues are separated into their own points, and personality factors are changed to demographic factors. Some points from Ali et al's (2016) table were consolidated into one, for example positive expectancies were omitted, because it can be considered to fall under "background, traits, attitudes and experiences".

Table 6: Summary of user resistance factors by Ali et al (2016)

People oriented	System oriented	Interaction oriented
IT skills	User interface, ease of use	Perceived social loss caused by interaction between people and technology
Training	System reliability	Lessened autonomy
Background, traits, attitudes and experiences	Data quality issues	Psychological contract and new technology
Impact of internal and external influences	Ease of using a new system	Lack of organizational fit
positive expectancies	Task performance and decision making not improved	social influence
individual and group level resistance	Not enough user involvement in the design and development process	uncertainty
changes in job content (can be countered with training)	Experience based perceptions	
demographic factors (age, education, needs, communication...)		

From table 6 above we can see that user resistance factors are many and varied. System providers need to take lots of factors into account when developing their software, and likely there are even more factors to user resistance than the ones depicted by Ali et al. (2016).

3.2.5 Gaps between leadership, data experts and end users

First of all, in order to take advantage of data, a company needs leaders who have a clear vision and knowledge on what information should be derived from the data and which approaches could be appropriate. This is something many companies struggle with: a lack of vision and not asking the right questions (Khalifa, 2019; Shao et al., 2022; Vassakis et al., 2018). In addition to leadership lacking vision, Stieglitz (2018) also notes that often, there is a significant gap between the data researchers and the field of research. Garoufallou & Gaitanou (2021) present a similar issue; they note that data analytics software often lacks contextual information about the user and their motivation. When there is a disconnect between the data insight users and the people

who generate them, the result can be the collection of wrong data, presentation of data in the wrong way, or both.

Sometimes, software providers fail to do proper user research, which can lead the product or service to cater poorly to the users' actual needs. If the system fails to answer to what the user wants from it, it can lead to users' decreased productivity, unhappiness, low sales and customer retention, as well as a poor reputation (Baxter et al., 2015). Successful connection between the development team and the end user, as well as involving the end user in the development process leads to a product that truly caters to the users' needs and wishes (Baxter et al., 2015). This in turn leads to more productive, happy users who need less support and training, higher customer retention and new sales (Baxter et al., 2015).

With the evident benefits of proper user research, it might be difficult to imagine why companies would neglect the subject. Baxter et al. (2015) list many reasons as to why companies might overlook or avoid user research:

- Perceived lack of time
- Perceived lack of money
- Disregarding difficulties in product use as user stupidity
- Claiming that users don't know what they want, so it's futile to ask them
- Claiming that because the product is new, there is nothing to conduct research on

The above are not all of the possible reasons listed. All of the reasons are not listed here, because it is not relevant in this thesis to dwell on each reason, rather than to demonstrate that the reasons are varied. Baxter et al. (2015) offer in their book counterarguments to each point, offering feasible solutions to the perceived issues with user research. For example, if a company claims that they don't have the time to conduct proper user research, Baxter et al. (2015) counter the argument by stating that even a little information is better than no information, and that it is very easy to find cases where product development went wrong and could have been saved with user research.

Un and Price (2007) consider in their paper "technology first"-developed products, surfacing another reason why companies might neglect user research. They argue that, sometimes bright minds are very eager to innovate the technology and they do not incorporate user or market research until they already have something tangible. And, as Un and Price (2007) point out, at that point, any evaluations made tend to answer why people might like a product, but fail to assess how people would actually use the product or how it falls short of user needs or wishes.

Yet another reason for disconnect between the end user and the development team that Baxter, Courage and Caine (2015) bring up is the lack of properly involving the product team. They argue that product teams can resist user research if they feel like they don't own that part of development. Burnes' (2015) theory of Depth of Intervention applies here as well - people are more likely to reject concepts or processes that they are not involved in. Un and Price (2007) further add that even engineers, who one could intuitively think do not need to know anything about the users, should understand the users' needs, wishes and aspirations to understand how they affect the product's functionality and tangibility. For example, if the engineers of a system designed for the elderly do not know their users, they might implement too complex systems, unless a service designer or someone else responsible for product design intervenes. Developing the wrong thing and having to redevelop the system costs time, and consequently, money. Having the entire product team to be aware of the users helps to avoid such mishaps.

While it's easy to assume that the disconnect happens only between the service providers and end users, the root cause might sometimes be higher up. Ali et al. (2016) list lack of organizational fit in their reasons as to why people might reject a system. There might be cases where a company tries to adopt a software that it's not ready or well-suited for. Why a company might not be good for adopting a software could be because of a number of reasons, for example, technical requirements or company culture. Newhook et al. (2016) note that enterprise software is often bought by CIOs (Chief Information Officers), or someone in a corresponding position. This means that the software is not chosen by the end users, which might lead to the purchased product not answering to the end users' needs. It might be tempting to purchase the most seemingly technically advanced product with the most features, without considering whether the end users actually benefit from all the available features or are they just complicating the software, making the users' work needlessly more complicated, lowering efficiency and overall user experience. While the responsibility for the decision to adopt a new software is ultimately in the hands of the client, the service provider should do adequate research on the prospect to determine whether they're good fit for the system. An ill-suited client company can lead to the very same issues as an unhappy individual user: implementation issues, increased need for support, frustrated users and bad reviews (Baxter, Courage and Cain, 2015).

3.2.6 Wrong or uncontextualised insights

The last found challenge related to data analytics was wrong and/or uncontextualised insights. Hariri et al. (2019) note that due to the poor quality and handling of data, the presented insights can be missing critical information, such as timestamps, which in some cases can be the breaking point whether that data can then be used for decision making. Garoufallou and Gaitanou (2021) add to this issue by stating that analytics platforms often lack contextual information about the user and the use case for the data, which can lead to the analytics providing insights that are not relevant for the users.

3.3 Future important technologies and features for procurement users

Now that we understand users' current challenges with data analytics and consequently, procurement analytics, we can shift our focus to the future and consider emerging technologies and features in digital services that will affect procurement users as well.

The introduction of artificial intelligence (AI) in software has been arguably one of the biggest disruptions of how users use applications today. As such, most results when searching for answers to the research question in focus were centered around AI features. Thus, it is fitting we begin this section by considering the future implications of this technology.

3.3.1 Artificial intelligence

In this thesis, artificial intelligence features refer to features that leverage the capabilities of computational systems to perform tasks with attributes conventionally associated with human intelligence. In recent years, artificial intelligence has erupted in consumer and commercial use. With the introduction of ChatGPT by OpenAI, various AI-powered chatbots on websites and virtual assistants such as Microsoft Copilot, people nowadays encounter AI in their everyday lives and work environments. Various data analytics software providers have deployed AI in their products as well, using being "AI-powered" as a major selling point. While AI has established a foothold in the technology industry, its exact future impact on people is unclear, which has caused some unrest around the topic and lots of discussion within both the scientific and technology communities, as well as consumer social media.

Cheng and Jiang (2020) studied AI-powered chatbots in their paper. They found many benefits to the chatbots, with the most prevalent one seeming to be enabling users to have immediate and easy access to information, an insight also supported by the study of Lee et al. (2023). With human customer service, people often have to wait to get answers to their questions. If no live human-to-human chat service is available, which is the case in many data analytics services, including Sievo, users then have to find the information they're looking for by navigating the service platform. Or, they can contact support by other, more cumbersome means, such as an email. AI-chatbots are available to all users with no queuing, they understand open ended questions and are able to be objective (Cheng & Jiang, 2020). In addition to fast answers to questions, as stated by Lee et al. (2023), AI enables "ordinary" people to get insights from data without having to learn technical querying methods, increasing overall accessibility.

It should be noted here that chat bots in data analytics solutions such as Sievo are likely not meant for customer service, rather the main use case would be querying and asking questions about the data. As such, the benefit of immediate access is not highly applicable to systems such as Sievo. However, the advantage of reduc-

ing the needs for technical skills related to data analysis remains as a benefit of chat bots.

Another major advantage of AI is the automation of some of the tasks traditionally done by people. Task automation can and has existed before the recent trend in AI technologies, for example in the form of conveyor belts, water supply and more. However, AI has introduced expanded possibilities for automation. From writing a grocery list to driving people's cars, more and more tasks previously completely reliant on people are now being partly or entirely executed by a virtual engine. Data analytics users are also looking at increasing levels of automation and AI. Babar et al. (2025) argue that largely, automation has been seen as a complement to the overall user experience of digital services due to tackling issues such as increased technical skill requirements of employees and shortened response time requirements of customers. Additionally, they state that when some of the workload is automated, human workers can allocate their time more towards complex, contextual problem solving.

3.3.2 The mobile platform

Mobile applications have exploded in use as smartphones have evolved and become a part of our daily lives. Smartphones and their applications enable people to connect with friends, peruse new furniture or even turn on their robot vacuum cleaner from anytime, anywhere. Yet the literature research indicates that niche enterprise system providers remain hesitant to offer their solutions in mobile form. Enterprise systems in this context means applications and software that is not meant for commercial everyday use, but is largely used by employees of large enterprises for their work tasks. An example of such enterprise software could be Microsoft Excel. Giessmann et al. (2012) made their study over a decade ago, but already then they recognized that the rise of mobile was recognized in technology driven companies and most of them included mobile development in their future strategy. They noted that the greatest potential for MEA (Mobile Enterprise Applications) lied in support activities, such as controlling ERP (Enterprise Resource Planning) systems.

As the biggest advantages of mobile applications, Lee (2016) states the concepts of "anytime" and "anywhere", which refers to the fact that smartphones travel with users wherever they go, and thanks to a global mobile network, they can be used anytime. Mobile enterprise systems would also offer the benefit of lowering operational costs while increasing flexibility and shorten response times (Lee, 2016; Bal, 2013). Bal (2013) also underlines the importance of applications being always available, and adds the benefits of enhanced productivity, increased sales and overall better competitive advantage.

Lee (2016) states that ERP and SCM (Supply Chain Management) have tried to leverage mobile, but that users have not been happy with such enterprise systems. This is likely a factor of multiple reasons. Firstly, Giessmann et al. (2012) speculated that a major challenge for mobile is the technical challenge in extending a desktop

native software for mobile. Sievo, for example, was originally designed for desktop use and continues to be developed for it, which leads to a lackluster user experience in mobile because the design of the application is not device agnostic. Because of poor UX in the mobile interface, users are forced to use the application on desktop, reducing possibilities for the ever important "anytime" and "anywhere". These "hybrid applications" where the same codebase is used for all interfaces, typically require designers to make compromises and sacrifices in designs to accommodate all platforms (Newhook et al., 2016). Native applications, where separate codebases are used for different interfaces, typically yield a superior user experience, but are more expensive to develop (Newhook et al., 2016).

Newhook et al. (2016) claim that highly advanced mobile systems such as the iOS by Apple and Android by Google have raised bar of expected usability in mobile applications. They note that consumer applications set the expectations for enterprise software, which is supported by Giessmann et al. (2012), who note that employees who use a mobile enterprise application are not only enterprise clients, but they are private consumers as well. They use the same device (or in case of a dedicated employee phone, a similar device) to handle their daily tasks in their private life. Newhook et al. (2016) state that enterprise systems often tend to emphasize the quantity of advanced features over simplicity and usability, which leads to overly complicated software. One would think that if an application is complicated on desktop, it is even more so on mobile where screen space is more limited.

Bal (2013) explores splitting larger systems into their own separate applications by function: much like Google has separate applications for emails, cloud file management and navigating the world with a virtual map. While this kind of separation can be beneficial, it has immediately higher development costs, requiring separate codebases and development teams. Considering procurement analytics, while the users might execute many different tasks using the tool, it remains questionable to validate for entirely different applications for such functions. But, even in a more centralized solution, separate applications for desktop and mobile could help provide an improved user experience.

3.3.3 Personalization

Bal (2013) state that enterprise applications are becoming increasingly role-based, meaning that they offer different features and options to different types of users. Such personalization allows applications to cater to a wider set of users without flooding them with an increasing amount of information, all of which is not relevant to all users. Rajikumar et al. (2024) studied the future user requirements of digital libraries. In their study, they found that personalization was important element of a well-implemented library. Much like complicated procurement applications, digital libraries host a vast amount of information. In such environments, users might struggle to find the information relevant to them. Personalization addresses this issues by presenting the user with content that is relevant to them, and reducing the noise of redundant

information (Rajikumar et al., 2024).

3.4 Important design principles of the new technologies and features

Now that we are familiar with what literature has to say about what procurement analytics users' current challenges, as well as what technologies and features will impact them in the future, we can start looking into how the new factors should be designed to ensure their (and the users') success.

3.4.1 Designing for change management

As recognized earlier in the literature review chapter 3.2.4, people resist change in general for a multitude of reasons. At the core of the resistance, there is a general uncertainty of the change's effect on one's work, and in the case of new software, the effort required to learn to use the new system or features in one's work. As discussed in chapter 3.3.1, AI and with it, increasing levels of automation are going to impact analytics users tremendously and change their workflows with the systems. Thus, change management becomes an essential part of the degree of success with which the future features will be adopted by users.

Shang (2012) presents four general approaches for change management: directive, participative, supportive and coercive, which are briefly summarized below.

Directive	**Participative**	**Supportive**	**Coercive**
Use of managerial authority to impose change	Widespread participation by employees on the process of change	Providing employees with sufficient information and support	Forcing change on key groups

Table 7: Change management principles by Shang (2012)

Shang (2012) inspects these processes from the adopting company's point of view. However, by substituting the word "employees" for "users", they can be considered from the software provider's view as well.

Let's consider the directive approach first. In Shang's (2012) paper, the managers orchestrated the change, providing the employees with the necessary training and information regarding the new tool or process, as well as rewarding employees who complied with the introduced changes. Translating this approach to a software provider's point of view, the tool could be designed to be directive akin to the managers. The system could direct the users to a desired direction and provide them with the necessary information to use any new features. However, outright rewarding users for desired behavior would be difficult to detect and implement. One way of introducing such rewards would be the "gamification" of the system, that is, coming up with a reward system that would give some form of digital points to the user for desired

behavior, such as watching an instruction video.

In the participative approach, employees are heavily involved in the change process, enabling them a sense of control, commitment, efficient learning-by-doing, and heightened trust via two-way communication (Shang, 2012). This approach was also heavily advocated for by Burnes (2015) and Ali et al. (2016), though they called it "the depth of intervention". Applied by software providers, the designers could keep frequent communication with the end users in the development phase, ensuring their understanding of the product, as well as heightening their sense of control by being able to influence the product's features and how it works.

The supportive approach focuses on the organizational support. The approach leans on the company enforcing the new tool or processes, which enhances its value in the eyes of the employee (Shang, 2012). What's more, the approach advocates for strong support and guidance systems for the employees in case of questions (Shang, 2012). Instead of organizational support, there could be strong system support. The system could encourage the users to use the new tools and processes, and assure them of their effectiveness over the old ways. In addition, the system would feature widespread support for training and how-to-guides for the users, as well as contact points for troubleshooting. This approach would answer to a concern of Ali et al. (2016), who argue that one factor contributing to new technology rejection is the users' lack of understanding the advantages of the new system if they already have a system in place that works.

The coercive approach forces the employees to adapt to the new tools and processes by establishing consequences. For example, firing employees that don't comply and promoting those that do (Shang, 2012). This approach is the least applicable of the four for analytics software providers, as they don't have the means for extreme measures, such as firing people who don't use the system in the desired way. Rewarding users would be possible, similarly to the directive approach. However, these reward systems would probably be much less effective than those described by Shang (2012), where the employees could get promotions based on desired behavior.

Shang (2012) recognizes in their study that there is no universal solution to all cases of change management. Instead, they advocate for using different strategies for different target groups. Interestingly enough, they don't discuss the possible combinations of the four change management approaches. Intuitively, it would seem that an effective way to reduce resistance to change would be a combination of participative, supportive and directive. Participative, by including the users early in the development cycle, enabling their empowerment, ownership and learning of the upcoming features. Then, the system should be directive and guide the users towards better ways of working. And finally, the systems should have sufficient support in place to enable efficient learning, enhance trust in two-way communication between users and the software provider, as well as providing a support touch point for troubleshooting, decreasing frustration. Coercive practices can be disregarded due to them not being effectively

applicable from a software provider's point of view.

3.4.2 Learnability

If new features, such as AI, automation and even a mobile platform are introduced, they further expand the already complicated systems of procurement analytics. In order for them to be brought in successfully, it is important their learnability is at an acceptable level to enhance user experience and acceptance. Furthermore, as discussed earlier, learnability is an already lacking area in data analytics solutions due to their complexity, which further underlines the importance of learnability in future features. It is not in the scope of this thesis to develop the optimal learnability guidelines for Sievo's upcoming features, but rather recognize the importance of good learnability in the future technologies and features, as well as look into some high-level approaches of learnability guidelines.

There are many metrics that may contribute to a well-learnable system. Yang et al. (2025) list familiarity, generalizability, consistency, and synthesizability as the most widely recognized learnability metrics. However, they also add others that have been realized later and in their study, such as engageability, discoverability, understandability and instructiveness. Their study developed design guidelines for learnability for elderly users in mobile platforms, which is a fairly narrow focus. The need for developing learning guidelines for such a narrow focus arose from the fact that there are no universal learning guidelines for all software and users. Yang et al. (2025) found that learning guidelines are scattered, developed from different perspectives, with varying levels of granularity. Lastly, most learnability guidelines ignore the nature of modern product development where design's focus changes depending on the phase of development.

Yang et al.(2025) use partly a bottom-up approach to evaluate and address learnability issues. They found that this approach provides specific, non-universal insights on learnability factors. This approach could be suitable for Sievo, since the product is contained.

Leaning to Robert M. Gagné's eight-phase learning model, published in already 1965, Yang et al. (2025) recognize that learning happens in phases. They also suggest that one way of approaching learnability is to consider users in different stages of learning. Since procurement applications are very complicated, users are bound to be in widely different stages of learning the product, and thus this viewpoint could be important to keep in mind. Intuitively, since learning is gradual, maybe introducing and teaching the software should be as well.

Sarkar (2023) discuss in their paper how software simplicity and gradual introduction of features have been widely regarded as good solutions for the learning of complex systems. However, they question whether these approaches are indeed good design practices, or just ways for designers to evade confrontation with badly designed

interfaces. Sarkar (2023) recommends that instead of gradual introduction, that is, obscuring parts of functionality from the users in the beginning of use, software should reveal all content at once, and at the same time boast extensive learning touchpoints, but not in the middle of actual workflows. Instead of learning by doing, Sarkar (2023) claims that users should learn the features ahead of time, outside of actual use. This shifts learning from task-oriented to capability-oriented, allowing users to realize the full potential of the application and then choosing to learn what they will. Sarkar's approach would cater to to different styles of learning, and enable cognitively skilled users to be able to use the full extent of the application quicker. However, the less able or even just busy users would potentially be in danger of being overwhelmed and having too much responsibility over their own learning. What's more, complete training materials for an extensive product would potentially take lots of time to go through, and all users probably will not have to learn the tool completely.

Some combination of gradual introduction and out-of-application training materials could be a good compromise. New users should have a high-level understanding of what the tool is capable of, but they should be able to start using the tool without knowing every nook and cranny. The system could guide the users towards learning the most relevant features to them, but it shouldn't hide features or stop the user from exploring other whatever features they will.

Ali et al. (2016) suggests adequate training as countermeasures to the learning related issues. Shang (2012) supports this by advocating for directive and supportive change management, in which training is a key method of increasing user participation, investment and acceptance. While training can certainly help with adoption, one could question using training as the end solution to learning issues, which for example Yang et al.(2025) warn against. Instead, software providers could look into how to make the service easy to learn and user friendly in a way that minimal training would be required, reducing costs and increasing user productivity, empowerment and satisfaction as suggested by Kendrick (2019) and Rafique et al. (2019).

3.4.3 Artificial intelligence design principles

As established earlier, artificial intelligence has already made a big impact on various softwares' users. Since the technology and its features are already landing in procurement applications as well, it should be observed what kind of design principles should be applied in its implementation.

An interesting finding that Cheng & Jiang (2020) identified with chatbots was that social presence and entertainment had weak links to user satisfaction. This suggests that people recognize chatbots distinctly as tools, and not human conversation partners. Lee et al. (2023) found in their study similar results: ethics, humanness and responsiveness seemed to have little impact on user experience, while naturalness was observed as having a strong impact on it. Based on these studies, it seems that users do not need AI to appear as human, as long as the interaction flows smoothly. Curiously enough,

some studies strongly suggest that adding human-like qualities to an AI enhances user experience. Nass & Moon, (2000) and Castelo et al., (2018) as cited by Lee et al. (2023) as well as Gray (2017) all agree that the lack of perceived human emotions in AI contributes to lower trust levels towards the AI. Gray (2017) notes that because AI lacks intrinsic motivators that people hold in high regard, such as genuine concern towards others, people have a harder time trusting something that sees people as datapoints in a spreadsheet. Gray (2017) also notes that AI lacks vulnerability - if AI makes a mistake, it faces no consequences. One could argue that a consequence could be that people can stop using the AI, but the AI itself doesn't care about that; the people who developed the AI do. People in general value accountability, and with AI, it can be unclear who to blame and whose responsibility is to fix things when mistakes happen. All in all, it seems that there is controversy whether AI should display human-like empathy, ethics or vulnerability. Some studies show that displaying human-like motivations enhance users' trust towards the AI, but other studies state that the lack of the human factors in AI does not worsen user experience. It appears that people are very aware that AI is not human, but an algorithm, and they treat it largely like any other tool, such as a car or a screwdriver. However, adding humanity to an AI does not seem like a bad thing, either. Companies using AI technologies can then decide how human they want their AI to appear, comparing the positive implications to user experience to the cost of development.

Gray (2017) notes that people tend to be intrigued when they encounter a system with AI, but at the same time, they recognize that users are sensitive to mistakes made by AI in the early stages of use, easily stopping using the technology if it makes an obvious mistake. It would be then natural to think to make the AI as rigid as possible and only have it answer exactly what the user asks for. However, Lee et al. (2023) underline in their study the importance of serendipity when interacting with AI. They note that AI can impress users by exceeding their expectations through providing unexpected and useful insights. Kocielnik et al. (2019) support Lee et al. (2023) by arguing that hiding mistakes hides opportunities as well, which then undermines the serendipity of the AI. Kocielnik et al. (2019) noted in their study that AI models that try to avoid "false negative" outputs perform better than those that try to avoid "false positive" outputs. What this means is, an AI that incorrectly tells the user that an email contains a meeting request (false positive output) is better received than an AI that incorrectly tells the user that an email does **not** contain a meeting request (false negative output). This is because in the case of a false negative output, the cost of error recovery is greater for the user (Kocielnik et al., 2019). However, in data analytics software, there are also use cases where users might be more sensitive to false positives than in the case of meeting emails. Considering procurement, a false positive insight made by an AI agent might be incorrectly claiming that switching aluminum suppliers will yield savings of 1 million euros, while a false negative might be incorrectly claiming that switching aluminum suppliers will **not** yield any savings. If a user acts on the aforementioned false positive output, they might actually end up losing the client company money, if they mistakenly switched to a supplier that in reality costs more than their current one. Even if they didn't go through with the switch, just initiating supplier negotiations takes effort and time, and could potentially result

in a very negative picture towards the analytics AI when the supplier tells the client that their price is much higher that the AI claimed. Considering the aforementioned procurement false negative, the impact is potentially much smaller. The client company might miss on saving opportunities, but they will not outright lose money. So, while trying to avoid all false outputs might indeed hide opportunities as well as Kocielnik et al. (2019) warn, analytics providers have to be careful about their AI's false positives, because acting on them will have potentially substantial monetary consequences for the users.

To counter users' disappointment when an AI makes a mistake, Gray (2017) suggests that AI should be transparent about its capabilities. Kocielnik et al. (2019) suggest the same: they propose that AI providers should tell the users how accurate the AI is, use example based explanation and allow the users to control the performance of the system, though what they exactly mean by control remains unclear. Being transparent about AI'c capabilities help manage bloated expectations that users might have about AI, and in turn soften the potential disappointment if the AI makes a mistake (Kocielnik et al., 2019). This ties back to the discussed change management practices where we discussed how involving users positively impact their perceptions and adoption of new technology. Data analytics software providers could benefit from being transparent about their AI's capabilities, because that way the users know that the AI can make mistakes, and are more likely to double check the AI's claims. This way, the users can still get interesting insights from the AI, but will not blindly trust it, which lessens potential big mistakes made.

The level of trust a user has in a chatbot is influenced by the level of trust the user has in the system the chatbot is embedded in (Hess et al., 2009, as cited by Cheng & Jiang, 2020). Lu et al. (2016) as cited by Cheng & Jiang (2020) as well as Lee et al. (2023) also found that positive experiences with chatbots can result in a better product brand image and heighten user purchase intentions. These findings suggest that the experience with a chatbot influences the overall user experience of a given system, and correspondingly, the user experience of the overall system affects how the user perceives a chatbot within the system.

Cheng and Jiang (2020) found in their empirical study that people's biggest concerns related to AI-chatbots were privacy related. People were worried about their data being misused or used in unforeseen ways. However, in their literature review, they found that some individuals might trust machines more with sensitive information than their human counterparts (Sundar & Kim, 2019, as cited in Cheng & Jiang, 2020). Cheng and Jiang (2020) provide no explanation for the contradictive results of their literature review and empirical study on the privacy issue. On one hand, it is understandable that people are hesitant to give their sensitive data to an algorithm that functions in ways they don't fully understand. On the other hand, giving data to an algorithm might give a heightened sense of anonymity, since it is not human and cannot judge a real person or have malicious intents by nature. Considering data analytics software as opposed to retail websites, privacy is a smaller issue on an

individual level. Users do not handle their personal data in the software, so the only potential sensitive information is the prompts they feed to the chatbot. At that point, the user is willingly giving to the AI what they write as their prompt, so the possibility for privacy concerns should be extremely small. On a client company level, it is harder to speculate what kind of privacy concerns, if any, companies have if their analytics provider uses AI. I could not find any information or cases where clients were reluctant to yield their data to an analytics provider because said analytics provider uses AI.

3.4.4 Task automatization design principles

Bernhaupt et al. (2015) as well as Roto et al. (2019) note that little research has been made on automation's implications on user experience, as well as user experience's effect on the acceptance of automation. Roto et al. (2019) discuss that one of the possible reasons for this could be that people think that user experience does not have to be considered with automation features, since the users do not pilot the action. However, the very migration of conventionally human tasks to an engine affects the users tremendously, and does not erase their relevance. Automation shifts people's tasks to more strategic work, as well as monitoring, maintaining and intervening in the automated tasks (Bernhaupt et al., 2015; Roto et al., 2019). Roto et al. (2019), Frhöhlich et al. (2020) and Babar et al. (2020) all argue that it is imperative that people are kept within the loop, even when automation is increasingly introduced. They note that automation technology is not free of errors, and in occurrence of one people have to be able to take over. What's more, they note that having a strictly automated system is potentially very rigid: it operates within the frames of the algorithm and often cannot serve users' niche or spontaneous needs. Much like the removal of human cashiers removes the possibility of getting your groceries even if you're one cent short. In a situation like this, a human employee can still help the customer, while an algorithm will only look at the number, see that it doesn't match and refuse to let the customer proceed. Babar et al. (2025) support this view and add that seamless transition to human assistance when necessary preserves continuity and enhances trust in the service. They recommend that automation is best implemented when paired with human intervention possibilities, and with clear escalation paths to human agents.

Fröhlich et al. (2020) mention that automation-heavy software face a trade-off between convenience and the joy of interaction. They discuss that interaction and activity nurture meaningful experiences for people, and lessening human activity endangers that. Roto et al. (2019) as well as Sarkar (2023) support this statement in their studies, revealing that people can experience boredom and a significant loss of achievement as a result of automation. Sarkar (2023) considers that if applications become increasingly run by algorithms, user behavior would be steered by the algorithm and not the other way around. They point to social media, where contentis pushed upon users regardless of their wishes, resulting in very little choice for the user. Fröhlich et al. (2020) also mention that while automation promoters frequently bring up that the technology frees people to do other tasks, these "replacement activities" have not been yet well defined or researched. When conventionally human driven tasks are

handed over to a machine, the human employee has to search for engagement and meaning elsewhere, which might leave them frustrated and confused if they do not know where to find those attributes. At worst, people can feel like the automation engine has "stolen" their work and with it, their meaning, leading to a very negative experience towards the technology.

Roto et al. (2019) mention that, commonly, high engagement is considered to be a consequence of good user experience. Highly automated software cannot use engagement as a metric of good UX in the same way, or at least the touch points are much different. High engagement with automated features might even be an indicator of a bad user experience. Roto et al. (2019) discuss that automation does not erase errors made altogether, but they are different from human made mistakes. Bernhaupt et al. (2015) complement this by adding that automation features can actually increase human cognitive load to monitoring and interference needs, which is exactly the opposite of the goal of the technology.

Transparency is a sizable factor contributing to successful automation features. Fröhlich et al. (2020) recognize that algorithm-driven interfaces operate differently from human-driven ones, so the intent behind any recommendations or actions must be made clear to the user. They make a clarifying comparison to a self-driving car, which might drive differently to a human driver, and thus must make its intentions clear to other vehicles and pedestrians in order to operate safely and conveniently. Babar et al. (2025) support Fröhlich et al.'s (2020) view and emphasize that effective use of AI-driven automation features require explainable AI (XAI), which enables people to understand and trust AI-generated recommendations and actions. Fröhlich et al. (2020) emphasize that with learning AI systems, it is especially important the recommendations and actions are transparent, since their behavior can change over time.

Roto et al. (2019) mention that in work environments, users can seldom choose the level of automatization of their tasks, which likely worsens the user experience to a degree. However, customization options are possible to implement into automation and AI-engines, and many means could be taken into use in the introduction phase that could heighten the users' experience. Fröhlich et al. (2020) found in their literature review that gradually introduced automation functions have been received well. It is likely that gradual introduction makes learning to use and adopt the automation functions better, heightening the chance that the users are able to utilize the automation functions and focus on more strategi work themselves. To take successful automation integration even further, Bernhaupt et al.'s (2015) study found that support for user-induced automatic task migration clearly heightened the user experience. That is, when users have control of what they automate and to which degree, they are more likely to accept and utilize the technology. Lastly, Babar et al. (2020) found that trust in AI systems develop over time, based on the system's perceived accuracy, transparency, and the user's prior experience. This further underlines the importance of successful introduction of automation features.

Even after the introduction, user control and customization options are an important feature of well-implemented automation features. Babar et al. (2025) state that high

levels of trust, transparency and situational awareness (AI engine's ability to hand over tasks to people when necessary) is what differentiate automation from collaborative AI. Now, these attributes do not change the fact that machines are taking over some of people's manual tasks, but if the user views the engine as a collaborator rather than something that takes over their tasks, they are likely to have a more positive attitude towards it. Fröhlich et al. (2020) think that when working with an AI engine, it is important users understand when they can utilize the AI, when can they follow its recommendations, and when can they override it. Fröhlich et al. (2020) note that programmers frequently customize their tools according to their preferences. Now, programmers have a skill set that allows them to customize more tools than the average person. However, automation tools have wide possibilities for personalization and customization in the user interface.

All in all, it seems that good automation user experience emerges from gradual introduction, where the users are given control of the extent of automatization. And, even in highly automated systems, it is important that the possibility for human intervention is retained in case of automation engine mistakes or shortcomings. The engine should be transparent of its recommendations and actions, enhancing the trust of the user. Implemented with these attributes in mind, the users are more likely to feel empowered by the automation functions, and they can focus on complex tasks that require contextual ability and emotional intelligence.

3.5 Summary of literature review

Research question 1: Current challenges of data analytics users

The first research question concerned the current challenges of procurement software users.

The first finding was the amount of information in complex data analytics solutions, such as procurement analytics, which results in a few issues.

First, users struggle navigating the platforms and finding the relevant information. With the abundance of potentially interesting data, even when they do find relevant information, users don't know which would be best to utilize in their decision making. (Zhou et al., 2014; Stieglitz et al., 2018)

Due to the complexity of the software, they feature a steep learning curve. Users have to spend considerable amount of time in learning the tool and they have to be increasingly skilled in data visualization and analysis in order to efficiently use the tools Garoufallou & Gaitanou, 2021; Khalifa, 2019; Shao et al., 2022). This is especially problematic for procurement users due to their already expanding responsibilities (Shao et al., 2022). A high learning curve worsens the overall user experience and heightens the chance that the users will reject the system, as they feel it only complicates their work (Ali et al., 2016; Laumer & Eckhardt, 2012).

Although data is plentiful, there seems to be one key type of data missing from the analytics solutions: real-time data. There are use cases for when users need fresh data in order to make good decisions, but the software struggle to output it due to the

volume and quality with which data is being generated. (Khalifa, 2019; Stieglitz et al., 2018; Zhou et al. 2014)

Another major finding was that users generally struggle with almost anything new or something that changes their workflows, especially if they already have an existing solution the new solution is meant to replace. People resist change for multiple reasons, which include, for example, feeling out of control if the company forces changes on employees without including them in the process or the new change being too big of a change to people's work. Experienced professionals are used to relying in their own expertise and are reluctant to relinquish decisions to a machine. (Ali et al., 2016; Burnes, 2015; Khalifa, 2019; Shao et al., 2022)

The last factor contributing to users' struggles is lackluster stakeholder communication and involvement from both their managers and the analytics provider (Stieglitz, 2018). While the customer company's internal change management is out of the analytics provider's control, they still have to maintain touch with their users in order to develop the right product for them. It was found that especially in technology-driven products, it is tempting to boast a large quantity of advanced features over properly addressing user needs (Baxter et al., 2015). Mirroring this, sometimes the customer companies can be led by idealistic people who want to adopt an advanced technology though their organization and employees might not be ready for it (Khalifa, 2019; Shao et al., 2022; Vassakis et al., 2018).

Research question 2: future important technologies and features

The second research question was intended to probe which technologies and features will be important to procurement software users in the future. The main findings were artificial intelligence enabled features, mobile platforms and personalization.

While searching for literature on this question, the majority of recently written articles focused on artificial intelligence. The main advantages of AI features were immediate access and automation (Cheng & Jiang, 2020; Lee et al., 2023). AI-chatbots were found to enhance the overall user experience of software by being able to respond to customer queries immediately and around the clock (Lee et al., 2023). The immediateness might not be such a big factor in data analytics solutions such as Sievo, as the chatbots there are not commercial customer service chatbots, rather the main use case is querying data and asking questions about it. In data analytics solutions, the main benefit of AI-chat assistants is enabling non-technical people to query data without having to learn difficult new skills (Lee et al., 2023).

AI-enabled automation, on the other hand, enables automation of some tasks traditionally done by people. People can focus on strategic, contextual problem solving while an AI-engine takes over repetitive and simple tasks. Additionally, automation can potentially further contribute to reducing the need for technical skills. (Babar et al., 2025)

In addition to AI-features, papers highlighted mobile platforms. People use smartphones increasingly in their daily lives, yet enterprise systems are hesitant to offer their services on platforms other than desktop (Giessmann et al., 2012). And, is an enterprise system is usable on mobile, the user experience tends to be poor due to the desktop design not being device agnostic (Giessmann et al., 2012). Offering mobile touchpoints to users would enable them to engage with the software almost anywhere, anytime (Lee, 2016; Bal, 2013).

Lastly, some papers discussed how enterprise systems are increasingly role-based, bringing up the need of personalization (Bal, 2013). Relating to the trouble of too much information and system complexity, all information available is not relevant to all users, so personalization is a good way of serving the users content that's relevant to them and reducing excess noise (Bal et al., 2013; Rajikumar et al., 2024).

Research question 3: design guidelines for the new technologies and features

The last research question was focused on what should be kept in mind when designing and implementing the technologies and features discovered as the results of research question 2.

Change management emerged as a theme to manage integrating the AI-features while not worsening the already steep learning curve of large data analytics solutions. Regarding change management, it was found that there is no universal solution. However, considering what the analytics software providers can do, a combination of participative, supportive and directive measures could be taken, as put forth by Shang (2012) . Participative, by including the users throughout the development cycle (Ali et al., 2016; Burnes, 2015; Shang, 2012), supportive by having a directive system that would be guide the users towards better ways of working without limiting them too much, and finally, supportive by having accessible support for the users (Shang, 2012) .

Concerning learnability, literature lists many metrics that contribute to a well-learnable system. However, it was recognized that there are not universal set of learnability metrics, and each system should evaluate its learnability keeping in mind in its own context and users. (Yang et al., 2025).

Gradual introduction of features was the main way research suggested for easing the learning curve of complicated systems (Yang et al., 2025). However, some research challenged this and claimed that gradual introduction obscures full capabilities of the tool from the user and instead, learning should be done outside work tasks, which caters better to different styles of learning, doesn't interrupt workflows and realizes the full capabilities of the tool better (Sarkar, 2023).

Training was also suggested as a countermeasure to poor learnability, though it does not directly improve the system (Ali et al., 2016; Shang, 2012).

All in all, complicated systems can only be simplified so far without reducing functionality. Evaluating the system against some learnability metrics, identifying pain points, as well as considering gradual introduction in combination with well-organized training materials could all be measures that would ease the users' journey in learning the system (Sarkar, 2023).

Papers on AI features revealed lots of recommendations for implementing them. First, there was contradicting evidence on the extent to which AI needs to appear as human. Some studies suggested that humanness has weak links to user satisfaction with AI, while others claimed that human-like AI greatly improved the user experience (Cheng & Jiang, 2020; Lee et al., 2023). However, no study was found that would have claimed that human qualities, such as empathy, would worsen the user experience. As such, as long as the interaction with AI is smooth, human features are a plus, but not a mandatory attribute (Lee et al., 2023; Gray, 2017).

In case of AI-made mistakes, the best measures to counter it would be to present its capabilities transparently as well as provide the explanation behind any claims made (Gray, 2017; Kocielnik et al., 2019). This way, user are aware that the AI can make mistakes, will not trust it blindly and that results in fewer disappointments and temporal or monetary casualties for the user (Kocielnik et al., 2019). Transparency also allows for the AI to operate in broader scope, offering the users the possibility of serendipitous findings, which can contain additional value (Lee et al., 2023).

Some papers found that people have concerns about privacy when it comes to AI features (Cheng and Jiang, 2020). However, it was concluded that these concerns touch mostly on personal data, which is a small concern in procurement analytics software since the users input and analyze company data, and nothing personal. Regardless, privacy issues should be taken seriously as that might be a barrier for some to use the AI (Cheng and Jiang, 2020).

Finally, regarding AI-enabled task automation, it seems that good automation user experience emerges from gradual introduction, where the users are given control of the extent of automatization (Roto et al. 2019; Fröhlich et al., 2020). And, even in highly automated systems, it is important that the possibility for human intervention is retained in case of automation engine mistakes or shortcomings (Roto et al., 2019; Fröhlich et al., 2020; Babar et al., 2020). The engine should be transparent of its recommendations and actions, enhancing the trust of the user (Fröhlich et al., 2020). Implemented with these attributes in mind, the users are more likely to feel empowered by the automation functions, and they can focus on complex tasks that require contextual ability and emotional intelligence (Bernhaupt et al., 2015; Roto et al., 2019).

4 Results of the empirical study

4.1 Users' current challenges in data analytics software

Procurement is a field that heavily relies on analytics to execute its core purpose, which is achieving cost reduction. The interviews revealed multiple issues where data analytics software is lacking for procurement users. However, before moving onto the core problems of the software, it is good to pause and think about the overall challenges of procurement professionals, so that the troubles in the context of their work is understood.

4.1.1 Procurement professionals' environment and toolset

In the internal interviews, a repeating theme was that procurement's responsibilities as a function have grown, yet their funding has not, resulting in people having to do more with less and a heightened need for efficiency. While some years ago procurement was largely only concerned with saving money, nowadays the field has to consider other factors as well. The interviewees listed factors including, but not limited to: supply chain disruption management, risk management and sustainability.

While procurement's responsibilities have expanded, their working practices have not developed at a corresponding pace. Interviews revealed that procurement is still heavily human intense and immature in terms of technologies used. A lot of the worker's time goes to human-to-human interactions, for example asking suppliers questions with emails. These interactions are time consuming and repetitive. Procurement functions working in large enterprises face further restrictions from their overarching organizations: large corporations are slow to change and have rigid systems in place, hindering its workers ability to take steps towards renewing processes and tools.

Procurement professionals also have to work with a plethora of systems to complete their work tasks. Sievo's CEO stated that "*Lots of Sievonians would be shocked if they would see the reality of of what kind of tools and processes these people need to work with, it's very fragmented to multiple different systems. It's very archaic, user interfaces, and there's a lot of manual processes that are required to keep all of this together.*". This quote was reinforced by the customer interviews, where the customers listed multiple systems when describing their workflows and having to piece together pieces from fragmented systems.

The vast amount of information results in complicated systems

The first theme that emerged from both customer and internal interviews is the sheer amount of data available to procurement providers and users. Procurement providers have to go through rigorous processes of extracting the data, transforming it to a usable format and trying to offer all of the relevant data to the users in an discoverable and understandable way. Pulling thousands of files of data from many systems results in

overwhelming software, where data is plentiful, but the users don't always know what to do with it.

Data analytics users are exposed to so much information that decision making becomes difficult when users are no longer confident on which data points they should leverage in their decision making, and whether there is some relevant data that they simply missed. A product manager said the following in an interview: *"Their [users] work is not to find things, our work is to find things for them and then their work is to execute on those"*. Right now, it seems that a lot of the users' time goes into finding the relevant information. The amount of potentially useful data and the growing demand for procurement have resulted in data analysis software that is overwhelming for the users. Interviewees almost uniformly mentioned that systems like Sievo are quite complicated. Upon opening the software, the user is confronted with a plethora of dashboards and, in the words of an interviewed service designer, "a never ending navigation bar". A customer also mentioned the navigation bar, and added that in order to form a cohesive picture of the data for a given task, users must know what information is presented where and in what manner, indicating that interpreting the data once found is not easy, either. The customer also mentioned that there are very few people in their organization who can effectively execute that process, e.g. use Sievo effectively.

A customer revealed in an interview that their most experienced users don't even use the readily provided dashboards in Sievo, rather they construct the dashboards themselves in the "self-service'" module. Additionally, they said that *"there is a need overall to increase the capacity of our buyers to understand and use the information that's already in Sievo and to free them to make decisions that they would not normally make"*. Another customer mentioned after the prototype demonstration that *"I think that's very good, in that **hopefully** some of the end users would use the options that are available there"* , indicating that their end users do not use Sievo to its full capacity, either, and steps need to be taken in order for people to start using the tool more and effectively. The fact that the most experienced users opt to gain their insights manually, and less experienced users need to brush up their skills to understand the available data in the first place speaks volumes of how poorly optimized large data analytics systems are for their users. This is not to say that the software providers are bad, rather than they face an immense challenge of presenting the relevant data without leaving anything out.

Large and complicated systems slow down the users' work. A service designer noted in an interview that even simple tasks are complicated in systems such as Sievo, and the users have requested for shortcuts, such as approving for things on their phone. A customer said in an interview that they spend lots of time for manual, repetitive tasks, such as updating system bookmarks for tens of stakeholders every month.

Learnability and training

Complicated systems take more time to learn. As discussed in the previous section, Sievo is deemed complicated by both customers and Sievo employees. Sievo users are

exposed to a lot of training material, which, as a service designer mentioned, further underlines that the system is not usable as a "plug and play" but needs quite a bit of ground work before it can be adopted effectively.

One of the customers interviewed stated that even with the training material in place, the biggest blocker to their employees to using Sievo is the lack of training. It remained unclear as to why the customer employees are not trained enough. Potential reasons could be that they don't know about it or it is too time consuming. Either way, the complexity of Sievo has not been solved by the existing training material.

4.1.2 Global disruptions

When asked about the biggest challenges in procurement, almost all interviewees brought up global disruptions. The world is perceived as unstable with natural disasters, global pandemics and constant political turmoil disrupting supply chain operations. Procurement faces pressure to keep the supply chains running within an environment of little to no predictability. While the users have the need to react to these disruptions quickly, the systems they are working with are limiting them. They read about global disruptions from the news, but their implications on the supply chains have to be deduced manually. Procurement systems help little, as the data comes there at regular intervals, much too late to use it in the decision making when reacting to an overnight emerged disruption. A customer said in an interview that

"We're going to have to have very diverse sources of supply. We're going to have to be able to move that supply basically, at the flick of a switch from one supplier to another".

Intrestingly, when inquired about the need for real-time features, Sievo employees were not very excited about the idea. A product manager said something that directly contradicts the previous quote of the customer:

So you're not switching suppliers every day to optimize for momentary changes in supplier offering prices etcetera. So you don't steer an ocean ship with like micro movements.

Multiple interviewees stated that users don't need real-time data in their daily work, and while that might be true, there seems to be some degree of overlooking the importance of users' capabilities to respond to unforeseen disruptions in their supply chains. Multiple interviewees recognized that Sievo is overall poorly connected to external systems and listed it as one of the most important features Sievo should develop.

The CEO of Sievo stated that "*Why can't we create in the background this tariff scenario and when you wake up or come to Sievo, there's hey, Trump announced tariffs and we have created you the base scenario or what this means for your business. How amazing that would be? And we are quite poor in that.*". When asked about what is the blocker for developing such a feature, the answer was simply the lack of priorization of the feature on Sievo's part.

4.2 Future important technologies and features for procurement users

In the interviews, the participants were asked to list the most important themes displayed in the protoytpe. The results are illustrated in the table below:

	Cust-omer 1	Cust-omer 2	Design Team	Prod-uct Mana-gers	Cust-omer Succ-ess	Sales	VP of Prod-uct Mana-gement	CEO of Sievo
Connectivity				x,x	x,x		x	x
Personalization		x	x			x		
Collaboration		x						
AI-assisted work	x	x	x,x	x,x	x,x		x	x
Guiding insights			x,x		x	x,x		x
Community data	x	x	x	x,x		x,x	x	x
Actions from Sievo								
Finance view					x			
Savings realized							x	

Table 8: Most important features of the prototype according to the interviewees

From the above table we can see which themes the interviewees thought the most important. AI-assisted work and Community Data were picked the most, followed by Guiding insights and Connectivity. Customer and Sievo employee picks did not largely differ, they were unified in underlining AI-assisted work and community data. However, the pool of customers was very small, so this likely does not reflect all Sievo customers. Next, we will dive deeper into the topics and discuss the findings of the interviews in depth.

4.2.1 AI-assisted work

Let's start discussing artificial intelligence with how the topic emerged in the interviews. When asked about the future of procurement work, all of the participants brought up artificial intelligence as one of the key components in how procurement will shape during the next few years. in addition, all of the interviewees except for Sievo's sales function, picked AI-assisted work as one of the most important themes in the prototype.

Several interviewees brought up the "hype'" around AI features. Product managers said that they feel the hype is justified, as did the CEO of Sievo, stating that because AI will fundamentally change how data analytics is produced and used, there is and

should be a lot of noise around it. Sales mentioned they feel pressured by the market to produce better AI stories for sales cases and they have to weigh AI features quite a lot in the sales processes overall. The CEO of Sievo stated that AI rouses curiosity and its presence in products is a selling point in itself.

One of the interviewed customers said that their company has invested heavily in AI and towards "working smarter". The other customer recognized AI being a big factor in the future, but also stated that their company is not ready for advanced AI features yet. They said they know AI is important and that they have to change their outdated processes in order to leverage it effectively. Sievo's customer success interviewee complemented this by saying that *"the ones [customers] who really leverage the AI capabilities will become much more agile and will be able to leverage more data points than ones who stick to the person needing to make the analysis."*.

Next, let's dive deeper into the main factors as to why the interviewees thought AI is such a key factor.

Task and analysis automation

Based on the interviews, the biggest factor contributing to AI's importance for data analytics users is automation. The interviewees uniformly thought that in the future, more and more work tasks ranging from searching for data to initiating supplier negotiations are going to be automated, and AI is going to play a central role in that.

Before we dive deeper into the insights concerning automation, a small disclaimer is necessary. Not all automation is necessarily artificial intelligence. One could have traditional algorithms that automate tasks, but AI, an advanced algorithm itself, is increasingly replacing the traditional algorithms. In the context of the interviews, we are discussing AI enabled task automation.

AI-powered insights

There were a few types of automation discussed in the interviews. The first and the most prominent one was AI-powered insights. That is, AI offering readily digestible insights of the data for the user, such as savings opportunities or increased risk with a given supplier. Several interviewees talked about how the traditional data analytics that rely on the users depicting the data dashboards are going to become more obsolete. This is seen as the correct approach, since much of the users' time currently goes into finding the relevant data, depicting it, forming conclusions and only then making decisions. This analysis could be done increasingly by AI. A service designer of Sievo described the AI-insights as follows:

"*Instead of you making your own sandwich, somebody makes a sandwich for you. It's not a buffet, it's a restaurant with à la carte."*

To clarify the insights, figure 6 shows a simplified visual of how traditional data analytics looks like. There are lots of graphs for the user to decipher, which is a

slow process. Figure 7 illustrates what the AI-insights could look like. The software provides a list of identified opportunities or risks, of which the user can choose what they want to inspect further. There's a clear summary of the chosen insight along with recommendations for possible action. The user can still go back to the dashboard if they want to inspect the data closer.

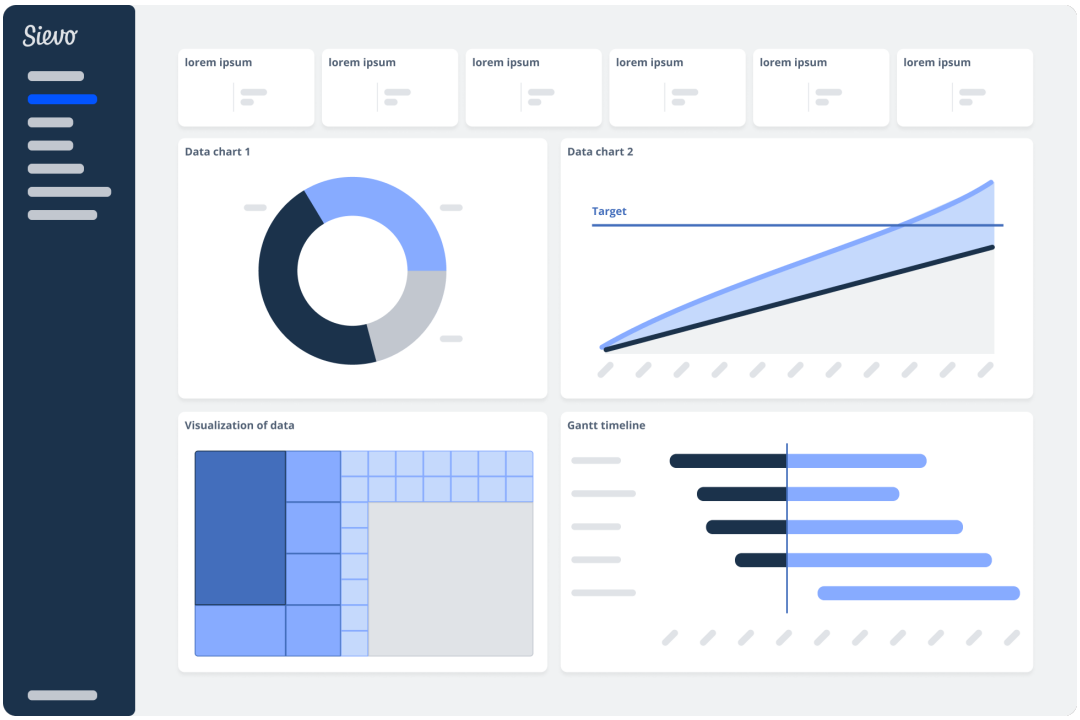

Figure 6: Traditional dashboard view - user has to interpret lots of complex visualizations

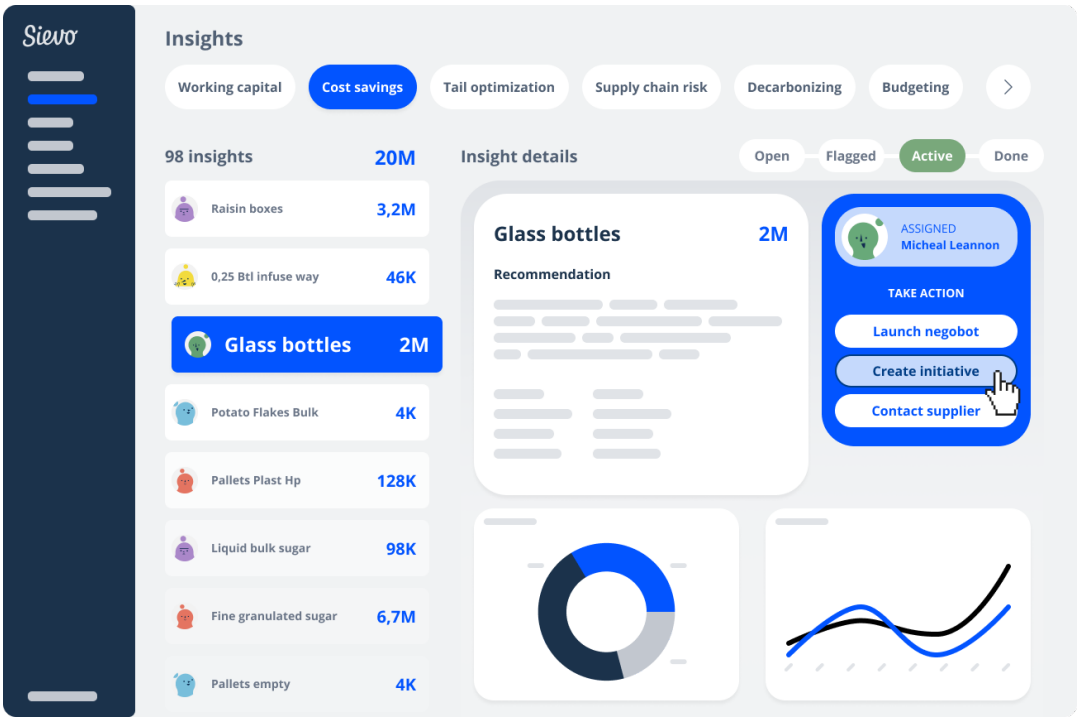

Figure 7: Intelligent insights - software tells the user what the numbers mean

In addition to automatic insights, the AI data analysis could also be prompted by the users for a specific purpose, for example a customer provided an example use case of pulling a spend report by entering an AI-powered chat bot:

"Sievo, can you pull me the spend report for January to March 2025 in this L1 category for this market. Boom, and then just have Sievo run the report and have it provide a bookmark to the report that we could use afterwards."

Automated data analysis is not restricted to one-time reports and queries. Interviewees talked about how users could set parameters for an AI engine, and the AI would then run the analysis on regular intervals.

Crucially, the interviewees feel that automated insights would save the users time and effort. The users wouldn't have to spend time crunching the vast amounts of data and try to construct something meaningful out of it. The vision is that Sievo would offer a selection of insights for the user, in a simple and understandable manner, much like a well constructed menu in a restaurant. The users would only have to digest the insights and then act on them, if they so choose. However, several of the interviewees also mentioned that insights would not completely replace data dashboards, as users would still need them for reporting and validation purposes, for example. However, reporting capabilities could eventually be in the scope of AI, so there's a possibility that in time insights would indeed completely replace dashboards.

Insights would also allow the users to uncover information they would not normally find. For example, an AI insight could be constructed based on unstructured data

and thus offer information to support decision making that was earlier not possible to take into account. Additionally, insights could provide the user with information they would miss, not because the data is unstructured or doesn't exist, but because there is so much information that insights would help the user to concentrate the amount of data.

An advanced version of insights would be guiding and actionable insights, e.g. operative insights that would suggest actions for the users in addition to presenting information. That means that the insights should not stop at giving the user information, but guide them towards continuing their work and taking action, whether that's contacting a supplier, creating a price forecast report on a construction material or keeping track of their KPI's. Several people suggested that upon opening Sievo, the system could present the user with operative insights and, for example, a "to-do" list of their most urgent items for the day. As the users have so much to do, Sievo could help users in prioritization. The interviewees emphasized that the system should guide the user through the potential actions as well, and not just pointing the user towards and action and then abandoning them: *"If the suggestion is that OK, go look at this dashboard, I think we are taking steps back."*.

Process automation

Moving on from data insights, AI could also be used for process automation. The interviewees felt that simple, repetitive, seemingly unimportant but mandatory processes could be handed over to AI in order to free the users' time for more strategic and contextual work. As an example, one interviewee provided an an example of how tail spend supplier negotiations could be one use case for such simple process automatization:

"They're suppliers providing pens or some paper or something. You don't even know who they are. You have no time to negotiate with them. So that part you could kind of completely automate to AI."

The CEO of Sievo brought up the same example, but enriched it by adding the benefit of collapsing the prices of supplier negotiations and accelerating procurement processes overall, since human time and effort would not be needed:

"People think that we should do things quarterly or annually because we are doing them so, but the real limitations are the people and resources available."

So, handing simple and time consuming processes to AI engines would enable Sievo customers to move at a much faster pace. They would be brought closer to real-time operations and decision making, since the majority of the manual work would be outsourced to AI at a fraction of the cost and directly proportionally increased speed. On the data analytics user's side, this would enable them to achieve cost savings faster, which is usually the ultimate purpose of procurement functions. Lastly, as discussed in chapter 3.3.1, with procurement's expanding responsibilities, this type of automation would be a major opportunity where AI can take some of the workload from people and they can then focus on the strategic work and complex tasks that require explicitly human attention.

In addition to automating tasks that slow down the human employees and their

processes, AI could be used to executing new tasks that are currently not done at all due to time and resourcing constraints. This type of automation would add completely new value for the users by bringing in data that is unutilized thus far. In the interview, the CEO of Sievo brought up the vast amounts of unstructured data that exists and is not being leveraged. They stated that for example, supplier interactions could be a "treasure trove" of information on supplier relationships and standings. Being able to access this data would better enable the analytics users to reach their goals in their work through more informed decisions.

4.2.2 Community data

Along with AI features, community data was seen among the interviewees as the most important future feature of future Sievo. While AI is important, it is something Sievo's competitors can do as well. Community data was viewed as the strongest differentiator of Sievo against competitors and do-it-yourself-solutions (DIY). The reason Sievo's competitors or DIY solutions can't replicate this data is that nobody has the same data Sievo does. Sievo has derivative rights to their customers' data, and with the volume of data that Sievo has (2% of all global GDP), that forms immense possibilities.

The value of community data is additional information to further assist decision making. This enables the users to, for example, benchmark their suppliers and performance against others in the community. The prototype had an example of comparing suppliers in several categories, and there was a possibility for further inspection. The customers gave very positive feedback on this, saying that this type of benchmarking would be very useful. They also thought that the community data would be a good place for discovery. One customer said that in their field, it is common to use suppliers just because they have been used before. The community data would enable easily accessible information about who's in the market, where the best prices are, where's the least emissions and other useful metrics. Combined with AI and actionable insights, the users could, for example, browse suppliers and compare them with community data, and then easily initiate contract negotiations.

One important feature of community data was not only showing data based on single points in time, but overall trends over a period of time. For example, how a supplier has performed over time, how have their emissions developed, how many customers have they had each year and so forth. This would enable users to make better long-term strategic decisions. Another use case was mentioned by a service designer who envisioned that this community data could somehow be accessible to the customers' suppliers as well, as seeing how they compare against others would motivate them to do better, resulting in better outcomes for everybody.

There is also the potential for addressing widespread global disruptions through the community data. In case of, for example, a large natural disaster, Sievo could through community data create scenarios of possible outcomes for all clients who

operate or have suppliers on the affected area. The work would be done once, and the information could be distributed to potentially hundreds of clients. Then, the users could rapidly gain an understanding of the current situation on a large scale, and act accordingly. This type of use of community data for insights would require real-time data integration, which we will discuss more in depth in the next section.

4.2.3 Reactive software and real-time data

When asked about the biggest challenges in procurement work, the interviewees almost unanimously named global disruptions and the inability to quickly react to them, as discussed in 4.1.2. However, Sievo employees were also asked whether they see use for real-time data, to which most said no. At first glance, it seems like Sievo employees then fail to see the connection between the problem of global disruptions and real-time data addressing it, but in reality, they recognize the connection and did provide lots of insights when discussing the global disruptions. The question about real-time data was asked late in the interview, and thus the interviewees probably didn't connect it to the issue to global disruptions. They stated that users have little use for real-time data in their daily work, because Sievo has been largely a long-term strategic tool as opposed to an operational one up until now.

A customer said that in order to be successful in the future, procurement functions need to become very agile and able to react quickly to changes in the market. Today, if there's for example political instability in some part of the world that affects supply chains globally, procurement professionals have to keep track of the events on the news, and then manually deduce what it means for their supply chains. By the time data arrives to Sievo where the user can see some implications of the disruption, it is already outdated and the appropriate window for timely reaction and action was already several days ago. Thus there is a strong use case of Sievo reading real-time data and producing immediate speculative insights in the case of major supply chain disruptions that require immediate operative action. Combined with old data, it would be possible to detect potential future trends and implications, allowing the users to make better strategic decisions. A customer mentioned that it would be valuable to have these "what-if" scenarios in place so that they could act accordingly in case of an acute situation.

The Sievo sales function interviewees said that they get lots of questions from prospects on whether the data in Sievo is real-time. in reality, nobody in the procurement analytics space has a real-time tool, so being real time would be a competitive advantage. It is not something the customers expect as a given, at least from the traditional dashboard analytics, but since they ask about it, it seems that there is real interest towards it. However, sales also pointed out that because no one has a real time procurement application, the use cases for real-time data are most likely not fully realized either. As such, the matter shows much potential but requires further investigation about where else there could be value for the users than notifications about supply chain disruptions and some monitoring purposes.

Real-time data would, if not outright require, strongly open the use case for mobile integration. The interviewees thought that it would be useful to have Sievo integrated to a mobile platform, so that in the case of global disruptions or other immediate attention requiring events, the users could be notified, wherever they are. Additionally, the interviewees saw use for the users to monitor things or quickly check something in Sievo from their phone. However, a full-blown mobile application for procurement was seen as unnecessary. The interviewees argued that the strategic work done in Sievo is too complicated to warrant much usage on mobile. The uniform suggestion was that Sievo should be integrated to some mobile application that the users already use, such as Microsoft Teams or Slack. The next segment discusses Sievo connectivity to external systems more in-depth.

4.2.4 Connectivity

Connectivity was one of the themes presented to the interviewees in the prototype, and it gained a fair amount of interest, although not as much as AI-assisted work, insights or community data. Within the prototype, there was demonstrated how users could be better connected to each other inside Sievo, as well as to outside systems, such as Slack, which is a communication tool. The internal connections was seen as helpful in enabling collaboration between users, but the connectivity to external systems attracted much more attention and excitement and this segment is going to focus largely on that.

The strongest message on the topic of connectivity was that Sievo needs to be where the users already are. The users shouldn't be restricted to be able to only query about their data in Sievo, but for example in Microsoft Teams or any other platform they already use. Embedding a Sievo AI-agent to Teams would enable the users to access their data faster, pull reports with a single prompt and get notifications about changes in the market, all in one accessible platform they know how to use. A product manager even suggested an extreme vision that Sievo would not be the place there the users access the information at all:

"If I were to be a little bit extreme on the visionary side, I would say that it could be that Sievo is not the go-to interface that you open the screen to. Instead Sievo is the underlying data provider."

Whether migrating users completely out of Sievo is the far away future or not, the interviewees were uniformly of the opinion that Sievo data should be accessible from other platforms via advanced AI chatting capabilities. The interviewees thought that due to Sievo still being a largely strategic tool, there are no grounds for a separate mobile Sievo application, but integration to an existing mobile platform for quick queries and notifications in the case of, for example, global supply chain events was considered a strong use case. This consequently surfaces the use case for real-time data.

The other type of connections discussed was data integrations into Sievo. Every customer is integrated into Sievo in a custom way, because Sievo doesn't have a

public rest API or other data interface the customers could easily feed their data to. Custom data integrations are time consuming and expensive. In the customer success function interviews, the interviewees said that this is what turns some prospects towards DIY-solutions. While this connectivity issue is related to processes before the actual use of Sievo starts, it is relevant to mention it since the issue lessens the users' reliance on Sievo and that can consequently worsen the overall image and experience of Sievo.

4.2.5 Other

The rest of the themes gained only one or two votes each when asking about the most important themes of the prototype. In addition, they did not gain much discussion in the interviews. As such, they are briefly discussed here and not given their own sections each.

Collaboration was mentioned as interesting by one customer and one service designer. However, the customer did not spend any time elaborating the theme, instead the ventured at length to others. The service designer who thought collaboration as important is responsible of a product team that's developing a feature that heavily involves multiple users in the process. Thus, their perception on the importance of collaboration features is much heightened compared to others. All in all, collaboration features can certainly be helpful and even important in some modules, but the feature pales in comparison to the ones discussed before.

Finance view, that is, procurement function turning their numbers into ones finance can use, also saw little interest. The customer success function selected it as an important theme in order for procurement functions to be able to prove their value to finance, who, in the end, hold procurement's budgets in their hands. To most Sievo end users, this feature seems to spark little excitement, though its existence would not certainly hurt.

Finally, outcomes tracked was included in the most important features by the VP of product management. They underlined that, again, admits increasing competition and the rise of DIY-solutions for procurement, Sievo needs to prove its value to its clients. This feature would help with that proof, but for the users, this feature would be useful mostly for reporting purposes. As such, again, the feature's existence wouldn't hurt, but its development is less important than that of the other themes mentioned before. The "outcomes tracked"-feature would be relatively easy to develop, but the prerequisites for it are the demanding part.

4.3 Important design principles of the new technologies and features

4.3.1 Change management

The importance of change management in regards to the future features was already discussed in the literary review chapter 3.4.1. However, the topic surfaced in the interviews as well.

The customer success interviewees stated that the features the prototype showcased would require huge change management on the customers' side, as they would impose major shifts in ways of working with Sievo. As such, they thought important that the initial experiences with the new features were as pleasant as possible to encourage the customers to use them.

Sievo customer success pointed out about the prototype, that if it was shown to a customer, they would be excited about it, but if they were confronted with the real software and told to start using it, they would have struggles and hesitations. The customer interviews affirmed as much, as the customers were excited about the AI features and recognized them as important, but at the same time, had many uncertainties about the new concepts. Their companies are not ready for what was displayed as is, but they are moving towards it gradually. A customer said that *"It's nice to offer the moon, but start with smaller small steps"*, emphasizing that they agree with the vision going forward, but are not ready adopt it as presented.

Since there is much discussion and "hype" around AI, it is worth considering whether AI is being implemented for the sake of the trend, and not according to user needs. Sievo's CEO said that there is risk with exposing users to AI quickly, but that it is a risk worth taking. They evaluated AI as a fundamental change in the procurement and data analytics landscape, and that with every major technological breakthrough, software companies need to evaluate whether the new trend is a momentary disruption or a fundamental shift within the industry. The CEO stated that the situation was similar a few years back with blockchain, but back then it was evaluated that it was only a momentary boom, and thus not worth investing in. AI has already proven major change, so even at the cost of user requirements, AI must be implemented and swiftly. Sievo's VP of product management also recognized that AI must be implemented, but emphasized that AI must not be just thrown to users for the sake of it, but consider carefully where it is needed and actually helps the user. So, the AI features will inevitably reach the users, but it is then a question of how it is implemented and introduced to make the adoption successful.

Because AI is a new technology and introduces a new way of working, it presents a challenge for user adoption. One of the customers interviewed felt that their company is a conservative one, and they are not ready for advanced AI solutions. The interview with Sievo's sales function affirmed this, saying that many customers understand the

value of AI, but they shun away from it, because it is too complicated too soon when they are still looking for the basics for their procurement management. In a sense, for many companies, AI is still a hammer looking for a nail. Taking advanced AI features into use requires robust change management within the client organization. Large, conservative enterprises have rigid processes in place that they might be reluctant to change, because it works. This mentality applies on an individual employee level as well; the other customer interviewed revealed that their company is enforcing its employees to integrate Microsoft Copilot into their work, but they haven't done it because they have an older, working system in place:

"I've set up a bunch of macros in Excel and that's my equivalent of Copilot. If I'm doing this that's taking me fifteen minutes to do, which is not bad, but it will take me forty-five minutes to try and set it [Copilot] up."

A service designer said something powerful in the interview when asked about the risks with AI; *Designing something that will then make the users lose their jobs... It's a scary idea.*

AI tools and features are all about making work more efficient. So efficient, in fact, that AI might eventually make humans obsolete. Even in the tasks that do not become dependent on AI alone, less human intervention and monitoring is needed, reducing staffing needs. Understandably then, there is uncertainty and even fear among people about the technology "stealing" their jobs. However, as the CEO of Sievo pointed out, with every major technical breakthrough, there has been resistance, because people fear what they don't know. Both Sievo's customer success interviewees and the CEO underlined the importance of easy adoption and change management with AI features and how it is the software provider's responsibility to drive the adoption of new features and ways of working. AI features need to be designed and introduced in a way that the users feel empowered by the features. One of the customers interviewed said that their company is reluctant to hand decisions over to AI, but to counter this, Sievo employees suggested that this could be managed by, for example, introducing the AI in decisions that people are not doing today anyway. This way, the AI is not taking decisions from people, but making additional ones. Introducing AI to the users gradually, and making the experience pleasant will encourage the users to use AI in their work increasingly, and lessen potential negative associations with it.

4.3.2 Learnability

Learnability was recognized as a central weakness of data analytics software in the literature review chapter 3.2.3. In section 4.1.1, it was discussed how both the customer and Sievo interviewees recognized Sievo as a complicated product and with a steep learning curve that training materials have not been able to mitigate. The need for a learnable software and sufficient training has one other amplifier: procurement professionals face the need for a larger set of skills. As discussed in the beginning of section 4.1, procurement's responsibilities are expanding and their tools are fragmented and difficult to use. Forcing the people in procurement to use complicated tools without sufficient adoption

processes in place is only going to make these users' lives more difficult, and in the face of the major additions of new AI features and more, the issue needs to be addressed.

When it comes to training, in the past, Sievo has done lots of personal trainings for users, but has since shifted towards an online education system where the users can watch videos and take tours around the product to learn it. In addition, support lines exist for any questions users might have. Sievo no longer provides human-to-human training of its products by default. This type of product education leaves the responsibility of learning more to the users, as opposed to human-on-human training. The customer success people interviewed expressed their concerns about Sievo's current processes for user adoption and training, saying Sievo might have "overstepped" on the matter and maybe needs to roll back on it to some degree. A customer said in an interview that the biggest blocker for using Sievo is the lack of training. As an experienced user, they gather quite a bit of information out of Sievo that is technically others' work, but they do it because they can do it so much faster than the actual task owners. However, they recognized that this way of operating isn't sustainable, and the effort should be made to train people properly: "*Teach someone to fish and they'll be fed all their life. Give someone a fish and they'll be hungry tomorrow.*".

As means to improve Sievo's learnability and ensure the new features do not become additional overwhelming factors, one service designer suggested gradual revelation of content and features. The specifics of how such gradual introduction should be implemented were not discussed, but the literature review chapter 3.4.2 provides some insights into possible options. However, the interview with Sievo's customer success function underlined that for retention it is important that users know what's possible in the tool and how they can achieve their goals with it. Sales also deemed showcasing the full capabilities of the product as important in convincing prospects that Sievo can solve their problems. Gradual introduction would obscure the full capabilities of the tool from users. What's more, the sales interviewees noted that most of the time, they don't get an actual end user into the sales call until quite late in the sales process. And certainly, they don't get all of the customer's users there. This means that all of the end users will not see the full capabilities of Sievo showcased in demo sessions. Then if the product is introduced gradually in practice, most user will not know what is possible with Sievo until much later, which might greatly hinder their effectiveness and user experience.

As well as the gradual introduction, the design team thought that the increasing AI features will actually help with the learnability issue. They speculated that since the AI would do the data processing for the user and provide ready insights on a plate, there would be less number crunching and data perusing that the user would have to learn. A customer reinforced this idea with the following:

What I like about that [Sievo AI insights] is... It takes the learning curve and puts it at a different place. So, today, if you look at our environment, the blue column on the left, [navigation bar] there is a plethora of dashboards. And you have to know what information is being presented in each dashboard and how it's being presented

in order to assimilate all that information into a cohesive story. And I have to say there are very few people in our organization who can do that.

AI-powered insights could help with the learnability issues of complex analytics platforms. While the users would still have to learn to use the insights, they are perceived as intuitive and much faster to learn to leverage than the traditional process of finding insights without AI. As well as the strategic insights, a guiding software, discussed in **??** could help with the learnability and masses of content in the software by providing a guided path for the user to follow. However, the AI features, while perceived as more intuitive than navigating a plethora of dashboards independently, are a substantial change to the users' workflow and thus introduce their own learning curve. What's more, it changes the entire product from a largely strategic tool to a potentially operative one. Thus, it is essential that it is kept in mind that the AI insights and guiding nature are new features and treated as such as far as the users are concerned. The AI insights are not going to immediately replace human data interpretation, but they will be an addition to the human made analysis.

In conclusion, gradual introduction to the product's workflows and specific feature use could be an option, on the condition that the user is first aware of what the tool is capable of on a high level. The training material should be easily accessible, and users should be able to contact Sievo employees for help or separate training sessions. In the farther future, AI could help lessen the manual work, and if by that time users have learned to embrace the AI features, their cognitive load would be overall lessened.

4.3.3 Artificial Intelligence feature attributes

Regarding the insights, one customer and the customer success people of Sievo thought that an important aspect of them would be that the reasoning behind the insights would still be accessible to the users. It was raised that in order to trust the given insights, users need to be able to validate them. For example, an insight that tells the user about a significant budget gap is not necessarily self-explanatory as is and the possible actions the user should take depend on the reason behind the budget gap. The reason could be currency exchange rates, tariffs or changes in supply and demand, for example. If the reasoning behind the insight is missing, a user cannot be confident in their actions and the insight loses much of its value.

In addition to decision validation, providing the why is an important factor in managing AI-made errors. Several Sievo employees stated that AI can make mistakes, and in some cases these mistakes might have significant monetary consequences. As discussed earlier in chapter 3.3.1, false positive insights from an AI can be risky in this sense. The risk for false positive insights increases with the serendipity of the AI, which also holds the most value, as discussed later in this chapter. The Sievo interviewees felt that the risk of AI made mistakes can be managed by having a disclaimer in the AI that the engine can make mistakes, as well as providing the reasoning behind any generated insights. The VP of product management said that ultimately, any decision making is the responsibility of the customer, even with traditional non-AI data dashboards that the user might leverage in their decision making. But, of course, the possibilities

of mistakes in the data or an AI engine should be managed as possible to make the experience better.

A customer mentioned that while insights could certainly be helpful, sometimes they can't act on them the way the software would recommend, due to, for example, industry or contractual restrictions. Nonetheless, the customer emphasized that even if they can't act on the insights, it's nice that they're there and it's something they can still look at and consider, especially if they can see the reasoning behind the numbers.

One theme that arose in the literature review was the value of AI serendipity against the ability to answer pinpoint questions. That is, the argument that ultimately, AI provides more value to its users with unexpected findings, rather than sticking to only answering exactly what the users asks for (Lee et al., 2023; Kocielnik, Amershi, & Bennett, 2019). This topic was raised in a few internal interviews to inquire about Sievo employees' feelings on the matter. At first glance, opinions were divided but after some thought it seems that the framing of the question lead the interviewees to consider one aspect more important than the other, while in the end, the participants agreed that serendipity in fact holds the most potential value, while the ability to answer specified questions is a mandatory prerequisite for any serendipity.

The VP of product management emphasized serendipity. They were of the opinion that asking questions from an AI accelerates the work, but what will bring the most value is the AI discovering completely new information and providing insights on things the user wouldn't have found themselves or wouldn't have had the time to focus on. The design team complemented this opinion, though they argued that serendipity is impossible to achieve without the ability to answer pinpoint questions first.

Sievo's CEO and product managers put more value on the ability to answer pinpoint questions. A product manager stated that they never start their day by going to an AI and asking it to think something for them, rather they always have something in mind already, comparing the AI to Google. However, a customer revealed in an interview that they'd potentially struggle with finding the right questions among the vast amounts of data, and AI could help with forming the questions, which is in itself very exploratory:

"But if we were able to, say, with the training and the how to frame a question, that you have to do anyway in order to use the analytics manually. You still have to know what the question is, that you're trying to answer. . . If you could build an application where you can ask the question there and maybe have the application help you frame the question and then go and do the analysis, and present the results back to you. Then, that would save hours of work"

This quote further underlines the users' struggle to find the relevant information within systems like Sievo, when they don't even know what is the root question they're trying to answer. Here, having an AI with serendipity would be extremely valuable, helping the users to find the relevant information with the right questions. Of course, the intelligent insights would already eliminate some of the need for the users having to know the question to ask, but in case of a chatbot, for example, it would need to be able

to help the user to utilize it to the full potential. If the users need to become prompt engineers in order to use the AI features efficiently, the AI is just adding another hard skill to the users' plate.

Lastly, there were insights in the interviews on specific things AI should not be implemented on. In important decisions, AI seems not trustworthy enough to handle things on their own. For example, important supplier negotiations should not be handed over to an AI engine. The customers expressed that AI suggesting things is fine, but the why behind the suggestion has to be accessible, and AI must not make any big decision without human approval.

4.3.4 Personalization

Personalization was featured in the prototype and it gained some attention. The advantages of personalization are not difficult to understand. It seemed in the interviews that it is a given that personalization helps to achieve better user experience. In addition, personalization is not an entirely new feature unlike many others discussed before, so the interviewees didn't feel like it is as interesting or needs to be discussed as much. Hence, this section is respectively brief.

The main benefit is to help the users to focus on what's relevant for them and filter out the noise. Sales gave feedback on the prototype that there were still too many features for the average user. Paired with the fact that all of the features presented are new to varying degrees, there is the danger of overwhelming the user and them having a negative reaction to the introduced features. Product managers added that the prototype doesn't feel focused enough and still leaves the user responsible of finding what's relevant for them. Together with gradually introducing the new things and leveraging guided user flows, personalization could really help the users to digest both the amount of data in Sievo, as well as make the adoption of the new features as pleasant as possible.

A product manager said the following: *"I think as long as Sievo is used by human beings, personalization just helps toning the noise out."*. The first part of the sentence again implies the increasing amounts of machines, that is, AI engines taking over human work. It remains to be seen how much can truly be automated with AI, but as long as there's people using Sievo, the product should strive for being as easy to use as possible, and personalization is a key component in that due to the amount of data in the system.

4.3.5 Connectivity and real-time data

As discussed in 4.2.3 and 4.2.4, there are use cases for users to access Sievo data through their phones, and some data, for example a global disruption's implications on the supply chain, should be available to users in real time so they can react quicker to events that require immediate action. With both of these features, the discussion was focused on recognizing the use case and not on how to implement such features.

As a consequence, there is not much empirical insights on the matter.

The access of Sievo through another system was thought in the form of a Sievo AI chatbot embedded into Microsoft Teams, or whichever platform the client company uses, through which the users could query and pull information. The design principles to take into account are the same ones regarding AI, discussed earlier in this chapter. Designing this kind of integration to another tool will also require collaboration with the other platform's development team, as well as consideration of how the feature best fits into the existing system. However, those processes are out of the scope of this thesis.

As for the real-time data, there was a clear use case for it: global disruptions' implications on the supply chain. There was not much discussion at all about how such features should be implemented, as the focus was on recognizing the use case. Some interviewees mentioned phone notifications about events that required immediate actions, but also wondered if users would be annoyed by such alerts.

4.3.6 Stakeholder priorization

In the literary review, it was revealed that data analytics software commonly suffer from the lack of connection between the end user and the development team (Garoufallou & Gaitanou, 2021; Steglitz, 2018). Sievo serves a concentrated variety of users, and the product development teams take it as a given that proper user research should be conducted to best serve the user needs, and the design team frequently engages in such activities. As such, it was not relevant to ask about whether different users should be considered in the development process, because the answer to that is an obvious "yes".

However, it was relevant to approach this issue from a slightly different angle. Since Sievo is putting major effort into future technologies, such as AI features and community data in order to differentiate against competitors and DIY-solutions, the sales or consideration attributes of the product have been the focus. Yet, serving and retaining existing customers is also very important. With Sievo having to find a balance between product consideration attributes and retention attributes, the sales function, product managers, the CEO of Sievo and the VP of product management were queried about how they consider the different stakeholders and their needs in their processes.

Consideration attributes begin from the very first few seconds that the potential customer glimpses the system, and there it was deemed very important that Sievo boasts "wow-effect" features. Those are, for example, a sleek look and state of the art AI features. Retention attributes, on the other hand, are something quite different. They are the set of attributes that keep the existing customers happy. These are typically more advanced and mandatory features that help the users in their daily work, but are not highlighted during sales processes due to being taken as a given or being "not exciting enough" to make the cut in the demo sessions.

The interviewees recognized that in order to succeed, Sievo needs to win in

both consideration and retention attributes. All interviewees agreed that retention attributes are important, as without them the churn rates of customers would denote any sales made. Since the value of retention attributes seemed to be taken as a given, with the exception of the design team, the focus was more on the consideration attributes. For example, one interviewee said that the super users of Sievo have been wishing for a certain feature in the home page. The wish has been heard by the development team, but sales attributes will be prioritized over the wishes of the super user. The home page is something always shown first in the demo sessions, so it needs to instantly display the sales-important features, such as an AI chat bot. The component wished for by the super users can be still featured in the home page, but it will land under the sales-important features, in a less central spot on the user interface.

The design team was the only one that clearly put more weight on retention attributes. As Sievo is traditionally a strategic tool, its designers have adopted the mindset that any features introduced must be carefully tailored to best cater to the users' needs. This leads to rather slow design and development cycles that do succeed in their purpose. However, due to the threat of DIY-solutions and increasing competition, now is a time when Sievo needs to focus on differentiator and sales attributes. The design team faces a question whether they too need to adjust their thinking. This is not to say that retention attributes should no longer be considered, but as the design team has not really considered sales attributes at all in their work, it might worth considering *adding* sales-oriented design practices into their work.

The sales interviewees discussed that they spend a considerable amount of time on prospect discovery, that is, figuring out what are the prospect's problems and how can Sievo address them. This process differs from the user research the service designers do, but unfortunately the interviews didn't allow for diving deep into the subject so exact comparisons can't be made here. Nonetheless, it seems that the design team conducts user research much more slowly, meticulously scoping user difficulties and possible solutions. Sales, on the other hand, has significantly less time to scope the current problems of the prospect, and they have to find the solution within what already exists in Sievo. The product demonstrated needs not only directly address the prospect's needs, but it also needs to prove to be better than competing services or DIY-solutions.

The design team and sales do not collaborate much at Sievo. This seems to be a place of great potential for both teams, as sales could feed user needs to the design team and the design team could then see if those issues could be addressed better in Sievo. The sales function and design team collaboration could also help the design team to adopt more sales oriented design processes where necessary.

4.4 Summary of empirical results

Research question 1: current challenges of data analytics users

The first research question concerned the current challenges of procurement software users.

First, the interviewees mentioned that procurement's responsibilities as a function are expanding, but at the same time, the employees' tools are not evolving at a corresponding pace and the function is susceptible to budget cuts. In essence, procurement has to do more with less, which amplifies the procurement software related issues summarized next.

The biggest challenge named was procurement employees' incapability to respond to live events that disrupt their supply chains. The world is perceived more unstable than ever, with political turmoil, pandemics and natural disasters being able to change things frequently and overnight. Yet, procurement software offers no support on such event's implications on customers' supply chains, leaving them to rely on the news and manual deduction on consequences.

The biggest issue regarding the users' daily work was the immense amount of information in procurement systems such as Sievo. This issue results in two further issues: a high learning curve and time consuming processes to construct insights out of the data. Sievo's product was uniformly deemed as complicated, overwhelming and having a steep learning curve. In order to effectively use the system, users have to spend lots of time in training. The very need for training seemed to be a blocker for the customer users to use the tool to its fullest, amplifying the need to make the product itself more learnable without training. And, even when the users know how to use the product, they have to spend considerable amounts of time looking for the relevant data and constructing a sensible narrative out of it, since the software only presents the data and doesn't help with interpretation.

Research question 2: future important technologies and features

The second research question was intended to probe which technologies and features will be important to procurement software users in the future. The discussion around this question was overwhelmingly dominated by artificial intelligence and the automation features in enables. The main advantage of task automation would be to allow the human employees to focus on strategic work and tasks that require human contextual, cognitive and emotional intelligence. In the interviewees mind, AI could be used execute two main types of tasks to start with:

1. Tasks that people do today, but are simple, repetitive and time consuming, yet mandatory to do.

2. Tasks that people are not doing today due to lack of time, resources or due to oversight. This could utilize untapped potential

The discussion was mainly centered on automation type number one, whereas the second type was only mentioned by few people in passing. Concerning automation of tasks people do today, the data insights were the biggest example of it: AI crunched numbers, visualized accessibly to the user. These insights could be, for example, savings opportunities, supplier risks, sustainability opportunities and more. There should be both automatically generated insights and possibility for users to set parameters and have AI deliver results on demand. The AI-driven insights would saves the users time and effort of finding the data, deciphering it and trying to form useful insights manually.

A more advanced version of AI-generated data insights suggested were operative insights. These are farther into the future, but are perhaps even more exciting than the strictly number presenting insights. What they would mean is that AI could suggest action on top of presenting numbers, and even act as a first touch point to the suggested actions. Operative insight would further save user's time, and steer Sievo from a purely strategic tool to a partly operative one.

The community data was also an exciting feature for users. The feature does not feature new technology per se, but it's advantage leans onto unique benchmarking opportunities for users due to Sievo's derivative rights to customers' data. The community data would enhance procurement employees' decision making by adding an additional metric to weigh.

The last notable exciting new opportunities for Sievo were real-time and connectivity. They are discussed together because they relate to each other. The interviewees felt that Sievo should be where the users already are, and that's services like Microsoft Teams. Ideally, a Sievo AI-agent could be embedded into these services, where Sievo customers could access their data easily without changing platforms. If Sievo was connected to such services, in the event of global supply chain disruptions, the users could receive notifications to their phone and would be able to quickly query for more information and action recommendations.

Research question 3: design guidelines for the future technologies and features

The last research question was focused on what should be kept in mind when designing and implementing the technologies and features discovered as the results of research question 2.

The first central finding is the critical role of change management when introducing new features, particularly those involving artificial intelligence. Both customer success employees and customers expressed that while there is excitement about advanced AI features, the scale of change required from the customer's side working practices is significant. Customers see AI as inevitable, but are not ready to adopt the new functionalities at once and suggested a gradual introduction. There are also fears fears about job displacement and loss of control if AI is thrown onto the customers too strongly. Ensuring that the users' first experiences with the new features are positive

and easy is seen as essential for successful adoption.

Learnability emerged as another major concern. Sievo, like many analytics platforms, is perceived as a complex product with a steep learning curve. Customers feel that to use Sievo efficiently and to it's full potential, extensive training is needed. At the same time, the company's shift from personal, human-led training to online self-service education has the customer success function voicing concerns about leaving the customers to fare on their own.

Gradual introduction of features was suggested as a way to improve learnability, but there is uncertainty between the tradeoff of revealing features slowly and ensuring users are aware of the tool's full capabilities. The design team believes that AI-powered insights could help address learnability challenges by reducing the need for manual data analysis. However, these AI features themselves introduce new workflows and require their own learning curve, so they must be treated as significant changes in their own right. The recommendation is to introduce AI gradually, focusing on empowering users rather than replacing them, and to ensure that critical decisions remain under human oversight. The users should be aware of the overall capabilities of Sievo to encourage learning and increase the value of the tool, but introduction of feature use could still be gradual to ease the learning curve.

Transparency and trust in AI-generated insights are also crucial. Users need to understand the reasoning behind AI recommendations in order to trust and act on them. In particular, with serendipitous insights, which hold the most ultimate value according to the interviewees, providing the why is especially important. The risk of AI-made errors must be managed with clear disclaimers, providing the why behind all insights and by maintaining user responsibility for final decisions. Ideally, an AI agent in Sievo should be advanced enough to help users through the entire flow, from formulating questions to presenting grounded answers.

Personalization was uniformly regarded as a given benefit, helping users focus on relevant information and reducing the overall overwhelmingness of the product. Personalization should be paired with gradual feature rollout and guided user flows to help users adapt.

There is also demand for connectivity and real-time data, particularly for responding to global supply chain disruptions. While implementation details were not deeply discussed, integration with platforms that the users already use, like Microsoft Teams, is considered the best use case for such features.

Finally, Sievo has tension between developing "wow-effect" features for sales (consideration attributes) and robust, practical features for existing users (retention attributes). Both are necessary for success, but the design team focuses more on advanced user needs and retention, while sales prioritize features that differentiate Sievo from its competitors. Currently, collaboration between sales and design is

limited, offering an potential area for improvement.

5 Discussion

5.1 RQ1: The users' current challenges in procurement analytics software

The biggest challenge of procurement software users found in the interviews was procurement software's inability to help the users in the case of global supply chain disruptions. The world is perceived increasingly unstable, so the users feel the need for agile work practices and flexible tools is heightened. Yet, complicated data analytics software, such as Sievo, do not support real time data and thus offer no insight to the potential implications of a global disruption on a customer's supply chain. The interviewees almost uniformly brought up the issue at least indirectly.

The literature review revealed related results, though not directly the same. Because procurement is a narrow subfield of data analytics, there was no proper literature or research done on the specific challenges of procurement users. However, researching challenges of data analytics users did bring up the lack of real-time data in large analytics systems. In the literature review, it was brought up that for example healthcare professionals have the need for real-time data in order to properly review the patient's status and take the correct course of action with them (Khalifa, 2019; Stieglitz et al., 2018). The same can be applied to a degree to procurement users, though the patient is substituted with the supply chain and the injury with a global disruption, such as an earthquake or a political conflict.

The reason for the lack of real-time data was discussed in some of the interviews briefly, and it seems that it boils down to lack of prioritization on the use case. Sievo was repeatedly described as a long-term strategic tool, and that could explain why real-time data has not been capitalized on. The interviewees also felt that because nobody else on procurement analytics has real-time data, the use cases and potential value for it are not fully realized.

The literature review on the other hand, pinned the lack of real-time data on technical limitations. With the velocity, volume and quality that data is being generated with, it would take huge computational effort to bring the data to the uses immediately (Hariri et al. , 2019; Zhou et al., 2014).

The second major issue for the users was the amount of information in Sievo, which results in a few problems.

First, because there is so much content, the resulting software is complicated to view and use. Navigating Sievo and finding the relevant information was described a rather expert task, with users having to know where to look for the relevant data and how it's presented in order to form a cohesive story. One of the literary review's main findings was also the complexity of the interfaces, highlighting that there is too much information for the users (Zhou et al., 2014; Stieglitz et al., 2018). What's more, literary states that different users have different interests from the data, and analytics software has done little in terms of personalization or prioritization of showing the content to users (Bal, 2013; Rajikumar et al., 2024).

The high volume of data and complexity of the interface results in a high learning curve. Sievo was described as overwhelming and having a very steep learning curve. Although Sievo has extensive training materials in place, users still named the lack of training as a blocker for them to use the product efficiently. The literary review also surfaced the high learning curve of large analytics platforms. There, it was discussed that this results in a heightened requirements of skills for the employees that work with the tool as well (Garoufallou & Gaitanou, 2021; Khalifa, 2019; Shao et al., 2022).

5.2 RQ2: Future technologies and features that will be important to procurement users

Most of the discussion and the findings on the important future features of procurement software was centered around artificial intelligence and the features it enables. All interviewees, customers and Sievo employees alike, started first talking about AI-enabled features. They did not talk about AI features as a possibility for the future, rather than something that will surely have significant impact within procurement.

In the interviews, the main use case for AI was task automation. The data insights were perceived as a better alternative for people having to find the relevant data, analyze it and draw conclusions from it, saving the users time and effort. The operative insights were seen as the next step, and would further streamline the users' workflows by providing options on actions the users could do, and possibly even touch points to begin to take the suggested actions. Thinking beyond data insights, further into the future, interviewees thought that other, fairly simple and repetitive processes could be handled by AI, such as low priority supplier negotiations.

The execution of simple, repetitive tasks was perceived as a good use for AI in both the interviews and the literature review. Both the interviews and papers, such as the one put forth by Babar et al. (2025) brought up the benefit of enabling the users to focus more on strategic work that requires contextual, human consideration. Overall, the literature review results indicated that task automation would promote accessibility and reduce the technical requirements of procurement employees, since part of the data interpretation would be done by a machine (Babar et al., 2025). The interviews affirmed this benefit, though they focused more on the overall eased learning curve than a reduced set of skill requirements.

The last use case for AI found in the interviews was executing manual tasks that people don't do anyway, unlocking new completely potential. This one was not very thoroughly defined. The main advantage would be to utilize unstructured data and bring in additional metrics for decision making. Another speculated advantage would be the easy acceptance from users, as this use of AI does not replace tasks done by people.

Moving on from AI, the the community data was an exciting upcoming feature for users. While it is not new technology, it adds a unique metric to the users' decision making by leveraging all Sievo customers' data and presenting performance met-

rics that users can then benchmark and review their own company and suppliers against.

The literary review named immediate access to assistance as one of the main benefits of AI, mainly in the case of service chat bots (Cheng & Jiang, 2020; Lee et al., 2023). The empirical research did not surface this benefit directly in the AI-discussions, rather it was brought up in the conversations related to connectivity and real-time data. It was perceived important that Sievo would embed an AI agent to systems that the users already use. This way, the users could pull data and reports accessibly and quickly. This connectivity would also enable getting notifications and inspecting data on mobile platforms, which could be important in the case of global supply chain disruptions. The literature review recognized the vast everyday use of mobile software, and discussed how enterprise systems struggle to integrate themselves to mobile platforms (Giessmann, Stanoevska-Slabeva & de Visser, 2012; Lee, 2016). The topic was discussed in the interviews, and the unanimous opinion was that Sievo shouldn't have a mobile application, because most of procurement work itself is too complicated to be done on mobile. However, integration to existing mobile services found support. In addition to a mobile platform integration, real-time data was connected to the ability to respond to global disruptions on the supply chain, notifying the user of such events and forming speculative outcomes of the occurred events, helping the user to understand the situation and begin to take the necessary action.

Personalization was seen as a given benefit in reducing the noise and helping the users to focus on their most urgent tasks. The literature review confirmed as much, noting how the papers discussed that enterprise systems are becoming increasingly role-based, and thus different users have different requirements for the software (Bal, 2013, Rajikumar et al., 2024).

5.3 RQ3: Design principles to guide the implementation of the future technologies and futures

Change management

Change management was the first emerging theme that should be focused on when bringing in the future technologies and features discovered in researching research question two. With AI introducing not only new features, but fundamental change to how procurement software such as Sievo is used, it was considered essential that Sievo pays much attention to ensuring the introduction of the AI-features is pleasant and users feel empowered by them as opposed to threatened. The literature review concluded that there are no universal solution to how change management should be done, but a combination of participative, supportive and directive measures could be taken (Ali, 2016; Burnes, 2015; Shang, 2012). Participative, by including the users throughout the development cycle, supportive by having a directive system that would be guide the users towards better ways of working without limiting them too much,

and finally, supportive by having accessible support for the users. Combining these practices with the interview-based suggestion of introducing new features gradually seems like a viable approach.

Learnability

Learnability was another surfaced topic that Sievo should pay attention to. The users need much training in order to use the tool efficiently, and while the AI-features were generally considered features that would help with the steep learning curve of Sievo by reducing the amount of manual data searching and interpretation, they still come with a learning curve of their own. Gradual introduction of the new features and the whole product (in the case of entirely new users) was suggested as an approach by the interviewees as well as the literature review (Yang, Gao & Wang, 2025) to address the overwhelmingness of the product. However, it is important that users would still be aware of Sievo's full capabilities to encourage learning it and increasing the perceived value of the tool, as argued by Sarkar (2023) in their paper.

AI attributes

The literature review found that in case of a chat bot, an AI-agent that displays human-like (polite, empathy, language etc.) behavior will likely result in a better user experience than a strictly machine-like agent (Lee et al., 2023; Gray, 2017). However, this behavior is a complement, not a requirement. Fluent interaction should still be prioritized over niceties (Cheng & Jiang, 2020).

AI features should be transparent, according to both the literature review and interview findings. To mitigate user disappointments, interviewees recommended that any AI features should have a disclaimer that it can make mistakes, and the user should understand that the final decision responsibility is with them. The customer interviewees felt that users should have access to the reasoning behind any insights and recommendations made by the AI, for validation purposes and trust enhancement. These requirement were also found in the literary review, in the papers provided by Gray (2017), as well as Kocielnik, Amershi, & Bennett (2019). A transparent AI also allows for more scope for its insight generation, which enhances the possibility for serendipitous findings, which can potentially hold much value, as both the interviews and the papers by Lee et al. (2023) as well as Kocielnik, Amershi, & Bennett (2019) indicated.

While AI can take provide insights and automate some simple tasks, interviewees felt that big, strategic decisions should be under human responsibility. And, even small actions should be approved by people, at least at the beginning, to enhance the users' trust in the AI agent. The literature review also found that people have to have the ability to monitor the AI and take over when needed (Babar et al., 2025; Fröhlich et al., 2020).

Connectivity and real-time data

According to the interviews, Sievo should be connected to mobile platforms that the users already use, to allow for quick notifying of immediate attention requiring events, and providing possible implications on the users' supply chain. Additionally, integrating to a mobile platform would enable the users to query data easily from wherever, whenever. The details of how to design such integration with external applications was not discussed, and is outside the scope of this thesis.

Stakeholder involvement

One of the literary review findings was that data analytics software suffer from disconnections between the development teams and users (Stieglitz, 2018; Garoufallou & Gaitanou, 2021). However, the interviews indicated nothing about users feeling that they are not properly involved in the development process. In fact, Sievo employees underlined that Sievo is quite good in considering user needs and involving them in the development process. Considering the disruption brought by upcoming AI features, it is imperative that users are kept within the loop in the future as well.

However, there appeared some stress between retention and sales attributes of the product, and only having easy access to a narrow set of users (super users). Sievo needs to win in both sales and retention attributes. Right now, the design team is largely focused on retention attributes, and could collaborate with the sales function to investigate the sales attributes as well.

5.4 Limitations of the study

A limiting factor on the view of customers was the very small sample of customers (two) acquired for the interviews. Although the larger pool of Sievo employees interviewed (ten) formed a good overall picture of the struggles and wishes of the customers, it would have been better to hear more straight from the source. A larger pool of customer interviewees would have likely given insight into how the different roles of users, such as buyers or category managers, affect their views on the topics discussed.

The fact that the interviews were ran as a part of the larger Sievo Vision project meant that the thesis researcher couldn't tailor the interview and its questions to best answer the research questions. As a result, some themes from the literature review, such as whether AI is better appeared as human or not, had to be dropped from the discussions.

The future is an unknown, and therefore the literature concerning future implications of data analytics was based on emerging technology, and all implications are speculative in nature rather than proven fact.

The AI at year 2025 is such an overruling factor when it comes to future implications that it might have buried some other future technologies and features that would have otherwise emerged.

6 Conclusions

Research problem: What design guidelines are important for future procurement analytics software?

This Master's Thesis set out to clarify what technologies and features are going to be important to procurement software's users in the future, as well as research how they should be designed in order to maximize their user experience. The research was carried out with a literature review, as well as an empirical part. The empirical research was done by interviewing both Sievo customers and employees, and the data from from the interviews was analyzed using qualitative measures. Considering the results of both the literature review and the empiric research, a few key themes emerged on how future features should be designed.

Design AI-features for human override and control as default. The interviews showed that AI is thought of not only as new features, but something that will, to a degree, change how procurement analytics is done. The interviewees saw the AI-features as an inevitability, not a possible part of the future. Although the interviewees and literature regard AI as important, there are also many uncertainties surrounding it. Consequently, AI-features need strong change management and reassurance practices to mitigate user resistance (Burnes, 2015).

When designing any AI-driven decision making features, such as supplier negotiations, users need to be able to take control as needed. The customer interviews indicated uncertainty and reluctance towards AI actually making decisions. The literature review likewise stated that human intervention possibilities are necessary, as AI is not error-free, and just having the possibility to intervene enhances users' trust in it (Babar, 2025).

AI-driven actions need to have control possibilities for the user, such as confirming before taking final action, audit trails to support accountability and the possibility to hand the work over to a human employee at any point.

Transparency of AI-driven recommendations and actions is a usability requirement for AI-based procurement analytics software. Both customers and the Sievo customer success interviewees felt that users need to be able to access the reasoning behind any AI-given recommendations and actions in order to trust them. If a reasoning is not provided, the users' trust is lowered and consequently, cannot act on the insights and they then have to manually verify such AI-findings, which undermines the entire purpose of the AI-insights. The literary review affirmed that transparency in AI enhances users' trust (Fröhlich et al., 2020) and it was also found that experts are used to relying on their on skills and thus reluctant to hand decision over to a machine (Khalifa, 2019; Shao et al., 2022). A significant portion of Sievo's users are procurement professionals, and so it can be expected that they too are keen to rely on their own expertise.

Based on these findings, all AI-recommendations and actions should feature

explanations behind the insights, and possibly other trust means, such as data lineage and confidence percents. Transparency also mitigates AI-made errors.

Treat integrated platforms and real-time data as accessibility contributors. The interviews found that a Sievo AI-agent should be integrated onto key platforms that the users already use, such as Microsoft Teams. This would enable the users to quickly view their data and get detailed information about it using natural language in a chat format, without technical queries. As these potential connected platforms often feature mobile versions as well, the users would have access to their data, whenever, wherever.

Users could be notified of global disruptions on these mobile platforms, reaching them wherever they are. The users could be told of a disruption's potential implications on their supply chains. This would answer the biggest challenge of procurement professionals named by most of the inerviewees; the inability to react timely and accordingly to supply chain disruptions. As an advanced decision making option, the software could feature a few alternatives on taking action and formulate speculative consequences of the offered actions. On large scale disruptions, quickly generated supply chain disruption implications could leverage a larger pool of customer data to offer insights to all potentially affected customers. This could enable many users to respond to supply chain disruptions at heightened efficiency.

6.1 Possibilities for future research

One of the main findings in both the literary review and interviews was that AI needs to be transparent about its actions and recommendations in order to enhance users' trust in it. The research did not delve into how exactly this transparency should be implemented, leaving room for future research. The AI-generated insights, for example, pose a major challenge here. The insights can be based on complicated mathematical calculations and deduction chains, which are in turn complicated to explain. How to achieve transparent AI while bringing the explanation behind recommendations and findings is going to be a complicated project, warranting much research.

Another thing that came up during the interviews was general uncertainty and even fear towards AI. This was not looked into thoroughly during research. It remains unclear whether procurement users have prominent concerns about AI and how those feelings should be addressed. If people perceive AI as something that will replace them, they will likely resist it. User resistance is obviously a great hindrance to any feature's success and with AI-features, it should be taken into account and properly addressed.

Lastly, the interviews found that Sievo should be integrated with platforms that the users already use, such as Microsoft Teams, to enable easy access to data and notifying them of quick action demanding events. However, the design details of this "Sievo outside Sievo" were not discussed. Integrating to another platform requires

collaboration with the other platform and careful user research. This is a topic big enough to warrant its own Master's thesis.

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