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Masterarbeit

Creating a Didactic Concept to Teach the Fundamentals of Artificial Neural Networks to PhD Students

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Abstract

Context: Given the recent stunning advances of applying neural network (NN) models in the context of science, it is natural for PhD students to show an interest in using these models in their own research.
Problem: However, in order for NN to be useful in research, one has to address the gap between the education about NN and the knowledge of how they can be applied.
Objective: The goal of this thesis is to elucidate what PhD students need to learn in order to be able to use NN successfully and to develop a concept for a game-based learning framework that achieves this goal.
Method: Through the use of a survey of Master and PhD students, we investigate what NN related competencies PhD students are interested in, what they need to learn and how they prefer to learn them. By then applying the resulting design principles and competencies to a concept for a learning game, we provide a prototype of this might look like. Finally, we provide an evaluation of this concept by interviewing representatives of the target group—PhD students.
Result: We show that the concept that we developed was judged positively by the interviewees. The design principles and competencies that we extracted from the survey seem to be to the satisfaction of students. However, it remains unclear if a game can deliver the high information density that PhD students expect while learning, given that they are subject to strict time constraints.
Conclusion: It appears as though the idea of a learning game that teaches NN holds merit and definitely can serve to increase the motivation of students that engage with this topic. Future work is needed in order to see if such a game, if fully implemented, truly can square with PhD students' expectations or if it is better suited for undergraduate level-teaching.

Contents

List of Figures

List of Tables

1 Introduction

The recent successes in the application of neural networks (NN) to a wide array of different problems, such as for instance protein structure prediction [JEP+21], image generation [RBL+22] or the recent popular large language models [BMR+20] have demonstrated their evident usefulness. The fact that they have already been successfully used on problems, previously thought to be too hard or intractable, shows that they hold great potential to be useful in scientific research, where they might support complex research topics like deciphering biological structures or extracting patterns from astronomical data sets [RA19].

To efficiently exploit this opportunity, it is necessary for scientists to not only possess profound expertise in their field of research but also to understand the underlying mechanisms of NN. In order to contribute to science, it is of great importance for prospective users of NNs to identify which tasks are well suited to be tackled by NNs, how to use them and how to read and interpret the results that a model provides.

However, there is still a gap between the knowledge of the application of AI and the level education in AI [LM20]. Hence, one educational hurdle that hinders the usage of AI in research is a general lack of competencies that are necessary for the effective application of AI methods. The term AI literacy has been coined by [NLCQ21a; ZVL20] to refer to the knowledge and competencies that are required in order to be able to utilise AI methods.

Because of the ubiquity and value of machine learning (ML) algorithms outlined above, any contribution to improving AI education is immediately valuable to a large audience. As PhD students are at the beginning of their scientific careers, they represent a group that greatly benefits from building their expertise in the field of NN. However, most of the research which aims at fostering AI literacy focuses either on primary or secondary education up to the undergraduate level of tertiary studies. Overall, there has been little research on increasing the AI literacy of people that have finished tertiary education and are now available in the job market or those that strive for higher tertiary education. The latter group is what we want to focus on in this work.

It is our objective to provide a concept of a game-based learning framework that targets PhD students in order for them to understand NNs and for them to be able to these models in their own research. Specifically, it is our idea to utilise the concept of gamification, i.e. the usage of game elements to positively enhance the learning experience. We aim to determine the optimal starting point for a didactic concept centred around NN, by figuring out common assumptions and existing knowledge in PhD students. In order to keep them engaged and motivated, it is important to determine the needs and expectations of students towards such a concept. This leads to our first research question:

Research Question 1 "*What does a didactic concept require to enable and motivate PhD students to learn the basics of neural networks?*"

After transferring the findings from above into a didactic concept, it is necessary to evaluate the introduced solution according to the students' needs. In our case, this entails the development of a game-based educational system.Thus the second research question follows:

Research Question 2 "*Does the usage of our proposed game-based approach motivate PhD students compared with existing and used learning tools?*"

In order to shed light on these questions, we will utilise the following methods. First, we perform a survey of prospective PhD students, as well as Master students to understand the requirements that they have with regard to the material that they want to learn about NNs, as well as their needs regarding a learning framework such as ours. In this survey, we focus not only on the content that they would like a course to contain but also investigate what motivates students to learn and specifically how game-like elements might help them get to those goals. Based on the results of this survey we define a didactic concept by integrating our findings with existing AI literacy frameworks in order to develop competencies and design principles that are the centre of our concept Our concept is specifically tailored towards teaching PhD students the basics of NN. After defining these theoretical components, we exploratory implement our didactic concept in form of a standalone educational game. We will then evaluate the introduced didactic as well as its proposed implementation with respect to our research questions. We aim to show that a game-based approach can be well suited to motivate students to engage with the course material and hope that our concept can be the basis of future work, where it would be implemented.

1.1 Contribution of this work

There are already tools, resources and courses on the topic of AI education. Some works as [KM98] focus on beginners and thus give a simple introduction into the topic of AI rather than in-depth insights. Others like [Sab20] aim to provide a more thorough explanation of the underlying technology. However, these are mostly designed as curriculum for schools or universities, where the self-study material is meant to be an addition to on-site lectures. There are learning platforms with modules on various ML topics. These modules on their own are self-contained and well structured. Still, most lack an overarching concept, which would arrange these modules in a logical context. This presents us with the opportunity to build upon a holistic concept, helping to guide the learner from start to finish. Several existing didactic concepts introduce game mechanics to help with the understanding of AI topics [RBM22; VZS+21]. These works clearly show the potential of gamification in educational contexts, a potential which we aim to build our approach on. Especially we target the exploitation of the thereby enabled opportunities to improve the learning experience and focus on the integration of theory with practice.

This thesis aims to design a didactic concept to teach the fundamentals of NN by keeping students engaged and motivated throughout the learning process. Instead of providing material that is most useful when accompanied by on-site or real time courses, this work focuses on a self-study approach. In addition to simply conveying knowledge, this work centres around shaping the learning process in a way that maximises the leaning experience for PhD students. To that end we will implement game mechanics, so that they directly weave theory into the concept, instead of only posing a complementary tool. Ultimately we aim to provide PhD students with the necessary knowledge to independently educate themselves further in the field of NN, e.g. by helping them understand subject-specific research and literature. This knowledge includes but is not limited to enabling PhD students to use NN as a method to solve specific problems, understanding the output and input structure of typical NN architectures and teaching them the underlying basics of algorithm and design choices.

The contribution of this thesis is thus the investigation of the topics that PhD students want to learn about in order to use NNs in their field, in addition to understanding motivating factors during learning. Furthermore, we contribute a concrete didactic concept for AI literacy and a conceptional proposal of an educational game, which incorporates our didactic framework This work addresses the existing gap in AI education for graduate students in higher tertiary education. We also provide ideas of what was deemed to be especially useful and what might need changing in an actual implementation of this game, which we obtained by interviewing PhD students and discussing our concept.

1.2 Thesis Structure

In order to investigate the problem stated above and describe our solutions and results, the remainder of this work is structured as follows:

Chapter 2 In this chapter, we review related work and provide an overview of the important topics in the context of teaching NNs and AI in general. We also investigate which existing competencies and design principles are useful and important in our concept.

Chapter 3 In this chapter, we provide an initial elicitation of requirements regarding what our target group expects a learning concept to contain, which explains the foundations of NNs.

Chapter 4 In this chapter, we summarise the competencies and design principles that fulfil the demands of our target group and which thus should be included in our concept.

Chapter 5 In this chapter we make a proposal on how the previously determined competencies and design principles might be used in the context of an educational game.

Chapter 6 Here, we investigate—by interviewing PhD students—how well the concept that we propose seems to be meeting their demands. And if a game-based approach is suitable for this task.

Chapter 7 After we discuss our findings and summarise all the results of the previous chapter, we conclude the work with an outlook of how future work might improve upon our concept.

2 Foundations and Related Work

The purpose of this chapter is to provide an overview of the context of our work. To achieve this, we will begin by introducing and defining key concepts for creating a didactic concept focused on AI topics. We then will provide an overview of existing research in the area of AI literacy and establish the boundaries of our work.

2.1 Background

In this section, we briefly go over the definition of AI machine learning and explain the most important terms and concepts of Neuronal Networks.

2.1.1 Machine Learning, Artificial Intelligence and Neuronal Networks

An often-used definition of *artificial intelligence (AI)* is to say that AI systems behave in ways that would be called intelligent if humans were so behaving [MMRS06]. This implies, that computers must possess various abilities, such as reasoning, planning, prediction, association, and perception, which allow humans to accomplish their objectives. AI is a field of computer science concerned with creating computer systems that can simulate and enhance human behaviour. [Bod16; Lo 20; RN10].

Of course, this definition is a very broad one, which is usually further partitioned into sub-fields of artificial intelligence.

An Overview over Machine Learning

One of the subfields, which is usually defined in the context of AI is *Machine learning (ML)*. Machine learning holds that instead of the traditional paradigm of computations, where explicit programs define the actions of a program, computers should instead be able to learn from experience. I.e. computer programs do not use pre-defined rules in order to arrive at a conclusion, but rather are given data from which they can learn to recognise patterns and predict the output expected from them. As such, a good definition of machine learning reads that machine learning algorithms are "autonomous and self-sufficient when performing their learning function". As the field that studies how to make computers infer—in an autonomous way—properties of data, ML is a central component of AI and is usually conceptualised in the context of AI applications, which makes them especially prominent [**ML-IBMa** ; Lo 20].

The aforementioned learning process is generally further distinguished into three training regimes, which differ in their degree of "supervision" [MRT18]: supervised learning, unsupervised learning and reinforcement learning.

Supervised learning is frequently used for classification, regression, and ranking tasks. This type of algorithm is provided with pre-classified (labelled) input-output data pairs, which are used in the training process for the computer to learn the mapping between the input and output. This mapping is then applied to new, unseen data to predict the output [CCD08; LW12; MRT18].

In contrast to supervised learning, unsupervised learning takes data that is not classified in any way with any labels and uses this unlabelled data for its predictions [Kub17]. Typical goals of unsupervised learning are, to obtain information by finding patterns and structures in the data set. Typical use cases of unsupervised learning are problems which can be solved by clustering, association, and dimensionality reduction [Kub17].

The third type of learning regime is Reinforcement learning [KLM96; Kub17; MRT18]. In Reinforcement learning the algorithm does not passively receive a data set. It rather collects information through a course of actions by interacting with an environment. The goal of reinforcement learning is to maximise some reward that the algorithm receives (or accumulates) by deciding which action to take in a given situation. Hence, reinforcement learning algorithms have to learn by obtaining reinforcement signals from rewards and punishments based on the actions that they take.

The typical use cases for this type of learning regime is in creating self-learning agents that are able to play complex games or navigate mazes [Kub17].

As machine learning is formulated fairly broadly, there are a large number of different methods that have been invented that fall under the broad category of allowing computers to learn. One of the most popular types of method is that of neural networks (NN), which has become increasingly widespread due to its apparent successes in a wide array of tasks. The recently published models that can generate text (for instance the ChatGPT models) or produce images of surprising quality have illustrated that NNs are powerful models, that evidently can learn from data and generate novel outputs. Nowadays, it seems clear that NNs offer the potential for solving a large number of very complex problems at high speeds [SS89]. We will give a short overview of the foundations of NN in the following section.

Foundations of Artificial Neural Networks

The term neural network stems from the fact that when originally envisioned, the idea behind them was to mimic some parts of how biological brains function. While NNs have been investigated for quite some time the recent advances are mainly due to very large models being computational—and conceptually—possible.

The term "deep learning" has been coined in order to describe this type of very large models, with a vast amount of neurons, which are in turn organised in a large number of layers, hence motivating the term "deep".

Now, we want to look at the actual structure of a NN model in more detail. Structurally, a NN consists of interconnected artificial neurons. These neurons are (almost always) structured in three distinct types of so-called "layers": An input layer, which will serve as the interface to the data that one wants the NN to reason on. Then, there are neurons that are part of the “hidden layer”, which are responsible for interpreting the data, finding patterns in the data and finally, an output layer, which as the name implies will contain the prediction that a NN makes, given some input [TSJ20].

The neurons in the hidden layer are connected to the preceding layer (either the input or another hidden layer in the case of deep networks) and in turn, connect to another layer of the network. After some number of hidden layers, they finally connect to the output layer. Each such artificial neuron or node has a threshold associated with it and each connection between neurons has a weight. The concept behind these artificial neurons, as was alluded to above, is connected to biological neurons, which have been shown to connect to one another and who—roughly speaking—can become *active*, provided their inputs from other neurons exceed some threshold value. This concept of *firing*, or becoming *active* is modelled by the use of an *activation function* which is applied to the raw output of a given neuron. This activation function not only models the biologically observed behaviour, where neurons stay inactive below the threshold but also increases the entire network’s expressive power [RN10; TSJ20].

Overall, a classification behaviour that a network displays is thus a result of the weights and thresholds (often called “bias”). Hence, the goal of training, i.e. the “learning”, is to find a set of weights and biases that result in the wished behaviour of the entire network [Kub17].

Operating a (trained) neural network by providing it with some input which then gets passed through the entire network, one layer at a time, is called *feed-forward*. In this way, they can be thought of as a function, which for each input x calculates an output y.

As mentioned above, the goal of learning is to make the output of the NN close to the wished output (often called *target*) by adapting the weights and biases inside of the NN. To achieve this goal, one needs a measure of how far the NN output is from this target, which is usually expressed in the form of a *cost function*. This cost function (sometimes also referred to as *loss*) is the conceptual distance between expected and real results.

Finally, training involves adjusting the NN weights and biases in such a way that the cost/loss becomes minimal. Formulated in this way, learning can be thought of as an optimisation problem, i.e. finding the minimum of the loss function by changing the adjustable parameters of the NN [Kub17; MRT18; RN10; TSJ20].

Historically, one of the main methodological problems stems from the fact that it is intuitively unclear how to deal with the hidden weights. Put into writing, this is equivalent to the question: How should the network’s weights in the hidden layers change to make the loss smaller? Luckily, there exist optimisation methods such as gradient descent, which require only a knowledge of the derivative of the loss function with respect to all weights including the hidden layers. This derivative can be calculated for any differentiable function by applying the well-known chain rule. As we mentioned above, NNs are functions and given that activation functions are chosen to be differentiable, those functions are also differentiable. As the derivative of an entire network is automatically calculated by the commonly used NN frameworks, we will not focus on this technical aspect here.

Finally, adapting the weights of all neurons by walking into the direction that the derivative indicates decreases the value of the cost function, is called *gradient descent* and the entire optimisation/learning procedure is often referred to as *backpropagation* [RN10].

We also want to mention that in practice, it is often unclear what specifically is the best choice of NN. One has a lot of different choices with regard to the correct architecture of a NN model, such as how many hidden layers to include, how many neurons each layer should be comprised of, or how large the steps should be that are taken during the training procedure etc. These parameters—which naturally might change the behaviour and accuracy of a model—are referred to as *hyperparameters*. In practice, choosing/optimising these hyperparameters is one of the main concerns in order to increase a model's usefulness for a given task.

2.1.2 AI in Education

5 Big Ideas

To close the existing gap in AI Education, initiatives such as *Ai4All* aim to define standards that future AI curricula should adhere to [23; TGMS19]. Touretzky et al. developed a framework by identifying the five key ideas of AI and organising them by when which grade level should know about an Ides. We briefly give an overview, of what their ideas entail:

1. One of the Big Idea is that computers perceive the world using sensors, and students should understand that machine perception requires extensive domain knowledge.
2. The second Big Idea in AI is that agents maintain models/representations of the world and use them for reasoning. Students should understand the concept of representation and how computers construct and manipulate them using data. They should understand: Reason with data but do not think like humans
3. The third Big Idea is about computers learning from data using machine learning algorithms. These algorithms allow computers to create their own representations from training data supplied by people or acquired by the machine itself. Students should understand that machine learning is a kind of statistical inference that finds patterns in data.
4. The fourth Big Idea is about the challenge of making AI agents understand and comfortably interact with humans, which includes tasks like natural language conversation, recognising emotional states, and inferring intentions. Students should understand the limitations of current AI in these areas — i.e. the currently limited ability to understand natural language and lack the general reasoning and conversational skills — and the importance of graceful interaction for robotic agents that will share our spaces
5. The fifth Big Idea is about the impact of AI applications on society and what future opportunities arise. AI can have positive and negative effects, and students should understand the ethical criteria that AI systems should meet.

Their ideas serve as guidelines for future education and many authors incorporated into their discussion about the definition of *AI literacy*.

AI Literacy

By the definition of [LASR22],"AI literacy" refers to the skills and knowledge related to AI that are essential for the general population to have. It is primarily aimed at individuals who do not have a background in computer science. A frequently used definition of AI-Literacy holds it to be consisting of a set of competencies that supply an individual with the ability to critically evaluate AI technologies and allow for constructive collaboration with AI tools in all currently used forms. Furthermore, following the work of Long et al. we specifically include in this definition the additional requirement for AI literacy to encompass the set of competencies that enable learners without a computer science background to understand AI technologies in addition to the definition stated above.

The term literacy is often used in analogy to classical literacy. Often, (see for instance [KSHH16; NLCQ21b]) authors compare the term to reading/writing literacy. This way, they emphasise that AI literacy should approach the standing of reading/writing literacy, which ideally should be taught early on, starting in kindergarten teaching and building up through university, given the importance of AI.

As stated above, AI Literacy is not only the theoretical understanding of AI methods but rather addresses other dimensions. Now we want to focus in more detail on the specific competencies found in the literature that are thought to aid in promoting AI literacy as stated above. Usefully, they might be sorted into different dimensions, as proposed by Kong and Zhang, whose dimensions and descriptions we now list[KZ21].

The first, dimension, called the *Cognitive Dimension* encompasses understanding AI concepts such as Machine learning and Deep Learning. This competency not only entails knowing and understanding these concepts, but it also deals with the usage of AI concepts for evaluation and real-world deployment, as well as evaluation of how well they perform for given tasks.

The second dimension, the *Affective Dimension*, mainly focuses on how students' emotions and perception changes during the learning process. With the stated goal of leaving students feeling empowered with what they have learned, they focus on building confidence in engaging with the AI community. Closely related to this component of AI literacy is the concept of *AI self-efficacy* the self-confidence of students when engaging with AI-related tasks. The authors hold that with greater self-confidence, students are more likely to continue working with/on AI systems. Furthermore, with the related concept of *meaningfulness*, the authors refer to the perceived relevance of AI in the students working life.

Furthermore, they focus on the *Sociocultural Dimension*, which focuses on the ethical part of using AI. The authors want to encourage students to use AI in an ethical way, which will lead to *sustainable global development*.

Another definition and categorisation of competencies entailed by AI-Litercy are done by Long and Magerko [LM20]. The authors based their framework on the 5 Big Ideas of AI and identified five important questions to answer when AI-Literacy: *What is AI?*; *What can AI do?*;*How does AI work?*;*How should AI be used?* and *How do people perceive AI?*.

Kandlhofer et al. [KSHH16] present in their work on AI-Education their definitions of the term AI literacy, which is more tailored towards to first understanding classical topics of computer science such as automata, graphs, sorting and problem solving by search.

As we can see, there are many facets to AI literacy. [NLCQ21b] summarised, that AI literacy generally encompasses four important abilities:

- Know and understand AI
- Use and apply AI AI
- Evaluate and create AI
- Discuss and apply AI Ethics

2.1.3 Gamifying Education

The idea of gamifying education has received widespread interest in recent years. Mostly, this interest stems from the idea of harnessing the entertaining nature of video games in educational settings. The hope is that in combining the desirable experience created by computer games with educational material one can make non-game material more engaging and motivating [DDKN11].

Introducing game elements into the learning process promises to motivate and engage students. argue, that the underlying logic behind this is, the hedonic nature of games that "focus on enjoyment, curiosity and immersion-[CR15]. Using such game elements in an educational context is believed to improve students' learning experience, enhance interest in the presented topics and promote participation in learning [NB22].

Unsurprisingly, the upsurge in interest has already led to the creation of different gamified education approaches. Kapp et al. have surveyed the literature and found that games provide a safe space for exploration, thinking and trial and error approaches and that they motivate students and can guide them, minimising their chances of failure [Kap12]. They claim that games are indeed ideal learning environments which not only encourage out-of-box thinking but also leave students feeling "in control", as they provide immediate feedback. Furthermore, they state that game elements leverage their inherent engaging factor to motivate students and stimulate students' imagination and provide a strong alternative to traditional direct teaching, or long textual explanations of a given topic.

Having looked at the general idea of gamification and the claimed benefits, we now aim to define the term more precisely: gamification describes the application of game elements in non-game environments to utilise the aforementioned anticipated positive effects of game elements on human behaviour [DDKN11]. In the context of education, this term, furthermore, encapsulates the hope of borrowing engaging game mechanisms and aesthetics in order to promote students' motivation and engagement with educational material. Kapp et al. furthermore note that this does not simply entail the usage of game elements, but rather a careful choice of elements to utilise game thinking on solving problems which aid the stated teaching goal [Kap12].

With respect to the question of what types of game elements are interesting from a perspective of gamifying educational material, Kapp et al. further emphasise that not, as is sometimes thought "badges" or the collection of virtual points contribute to the motivational effect of gamification. Rather, they argue, that the reason why people like games is mainly due to a sense of engagement, immediate feedback and the successful feeling after having accomplished a challenge [Kap12].

We also want to briefly discuss the term *game-based Learning*. game-based learning describes something closely related to gamification in general but is often thought of as distinct from gamification. Often, the terms “educational game” or — if used in an educational context — “serious game” are interchangeably used with “game-based Learning” [FMZ19]. Deterding et al. hold game-based learning to refer to fully-fledged games that are used in an educational context, whereas they define gamification only as the usage of game elements in an educational environment [DDKN11]. Similarly, Fatta et al. define *game-based Learning* as a combination of gameplay to enhance the learning experience and the delivery of purpose beyond entertainment — a defined learning outcome — for the educational domain [FMZ19].

Of course, this usage of terms entails a gradient of definitions, where gamification approaches might fall somewhere on the spectrum between simple usage of game elements to fully developed video games used in an educational context. However, [Kap12] notes that the envisioned goal is the same, regardless of whether a given medium is closer to game-based Learning or gamification: all approaches aim at solving the problem of increasing students’ motivation and promoting learning through “game based thinking and techniques”.

2.2 Related Work

In the following, we give an overview of existing literature dealing with didactic concepts on artificial intelligence; we specifically want to highlight the aspect of existing curricula found in the surveyed literature. Furthermore, we focus on their curriculum (AI education and literacy), game-type learning methods and tools to experiment and build NN.

Our procedure of finding research works, as well as our method of selecting papers to include in this section, was the following: We performed a cursory search for the keywords ÄI", Ëducation", ÄI-Literacyänd "Review". These terms were combined with the terms "Curriculum", "Frameworkänd "Game-based learning", SSerious game", Ëducational gameänd "Gamification". From these papers, we excluded all works that focused on the usage of AI Methods to support education, instead of focusing on educating about AI methods. Finally, using the results of our initial search and the review papers, we snowballed out to find further literature for our work.

Additionally, we searched not only for scientific resources on “Games for AI education”, but we also searched for non-scientific resources like games published outside of an academic context. In some cases, after finding such a work, we later identified scientific literature, that goes with a particular project. Next, we grouped the results in the categories “General AI-Literacy Frameworks”, “AI-Literacy curricula for K12 and university” and “AI-Literacy with games”, which are discussed in detail in the following.

2.2.1 Holistic AI Literacy Frameworks

The current increase in interest in the topic of AI literacy has caused the development of a great number of studies which focus on developing an AI curriculum. In Section 2.1.2, we listed frameworks that define AI Literacy and provide a general guideline for educators on how to approach the topic of AI. To understand the significance of AI in modern society and in education, one also might look at [CTP+18], where the authors discuss how existing curricula are impacted by the spread of AI in society and industry. I.e. how might e.g. a history class be changed to prepare students for a future workplace where AI is a topic.

Those frameworks provide a holistic approach to integrating AI in a K-12 curriculum, targeting all ages from kindergarten until high school or at most undergraduate university courses.

While some aspects discussed in these works are useful in our case, we certainly can not assume the same demands and interests in our target group. Furthermore, all works discussed here focused very generally on the aspect of AI instead of discussing the more narrow concept of NNs, i.e. there is no one-to-one mapping possible to our use case.

2.2.2 AI-Literacy Curricula for K12 and University

In ref. [KM98], the authors present a robot laboratory to introduce core concepts of AI in a course for undergraduate students in a top-down manner. While their approach is suitable to present beginners with first experiences, it is not thought to be a fundamental introduction to AI. Furthermore, their method is deemed to be executed on-site as opposed to an online on-demand type of course that we envision. Another projdect based approach with robots has been implemented by Williams et al.[Wil21], which can be programmed using a block-based scheme. This course contains a five-day online workshop for middle schools, requiring no previous knowledge of technology. Supposedly, the curriculum is beginner-friendly, with an emphasis on hands-on activities, including a physical robot, in order to enhance engagement. The teaching goals that are stated in this work are: creating consciousness about the usage of AI, understanding of AI, understanding ethical issues, the application of technical AI concepts to real-world problems, as well as teaching programming and construction of ML models.

Yet another work, by Burgsteiner et al., also utilises robotics to teach AI [BKS16]. In order to teach the fundamentals of AI, as defined in [KSHH16] this AI-Course is focusing on teaching the fundamentals of topics of AI-Literature. Their work also targets high school students and they provide their course material in the form of weekly two-hour units containing theoretical and hands-on parts. The hands-on parts include programming search algorithms, while the theoretical parts focus on the presentation and discussion of ML topics. Their stated goal is to familiarise students with the technical background and underlying concepts of AI on a foundation level.

Ref. [Sab20] describes another approach to teach AI, where—instead of a robot laboratory—the authors introduce a one-year curriculum meant for middle school lessons, including teaching materials. This approach is based on Five Big Ideas of AI (see Section 2.1.2), which they condense into three questions: the development of intelligent interfaces to communicate with human users (How do computers interact?), as well as computer-vision systems to see the environment (How do computers see?) and systems to understand speech and audio (How do computers hear?)"This work is more geared towards teaching ML in a traditional classroom setting, providing exercise sheets and lectures that are suitable for middle-school levels.

Evangelista et al. [EBB18] provide a short workshop for high school students. They describe their goal as "How can we address the machine learning topic in order to arouse interest on the topic but without relying excessively on mathematical jargon?" This workshop, which is partially in response to a survey presented in the paper, serves as an introduction to ML. Given that the course targets high school students, the author assumes that students have no prior programming experience. By illustrating a simple classification problem that can easily be solved intuitively, they make students realise the importance of training ML models from data, the concept of pattern recognition, the role of mathematics and ethical issues. The stated goals of this curriculum are to provide an introduction to ML fundamentals, aid students in understanding what learning means, increase interest in STEM topics, and provide students with a toolbox that can be used for further studies and projects.

Clarke [Cla19] provides a curriculum designed for classical classroom teaching. This curriculum was developed by the organisation called Exploring Computer Science, which ostensibly works to provide educational material for high school students. The material provided in this curriculum covers a vast number of aspects of AI usage, training and research, targeted to high-school students at the K-12 level. It is structured as complete lesson plans that can directly be used in school. This includes an outline of a lesson, the student activities, resources and a detailed teaching strategy. In this way, students can explore AI applications that might have an impact on daily life and also work on a hands-on project in the end. To summarise, this work aims to teach students about the applications of AI, going over relevant terms that are used in the context of deep learning and machine learning in general. It provides an overview of the social and ethical impacts of AI. However, all of the course material is geared towards a more high-level type of understanding, neglecting to teach the underlying mathematics or techniques.

Apart from the concrete teaching examples listed above, there are also more theoretical approaches and studies to teach NN.

With the AI-Atlas the authors of [SKGW21] introduce a didactic concept for developing an AI curriculum. They provide coherent best practices as well as guidelines and develop two courses aimed at university students (tertiary education): The ML-Learning course and the AI course. While specifically designed for on-site classes, both courses include online materials to be used in weekly labs. Instead of focusing on the development of one platform, the authors rather provide a framework of guidelines to develop a curriculum for AI. While they introduced didactic principles for their framework, they do not describe the content. I.e. they only provide theoretical foundations for an academic setting. These course materials are clearly thought of as going in addition to the classes.

The authors of [KCZ23] introduce a 30-hour-long project-based programme for university majors as well as non-majors. Their idea is to provide an AI literacy concept, which is geared towards improving the participants' conceptual understanding of AI, as well as empowerment and increasing their ethical awareness. They conclude their work with an actual study of their program on thirty-six university students.

The authors of ref. [ZVL20] provide a thorough review of the AI education literature of curriculum for the K-12 (high school) level. They sort core competencies found in those curricula and organise them in a way that aims to aid educators in finding resources for their teaching. Furthermore, they provide a conceptual framework to help future work in designing K-12 educational material.

We expect that research works that are categorised here are closer to our targeted application.

However, most works focused on a "normal classroom" setting with classical learning activities such as group work or exercise sheets. This is distinct from our envisioned concept, where we want to focus on self-study settings and utilise game-based learning. In general, we also note a lack of courses that teach a specific topic (such as NN in our case) in a short, intensive course. Rather, either the research works detail entire semester-long courses/lectures, or provide guidelines for short workshops that described AI in general.

These findings are also mirrored in the literature reviews that exist on the topic. First, as Ng et al. [NLT+22] note, it is also interesting to note that most of the research works focus on primary and secondary levels of education. They found that literature with a focus on tertiary education is rarer. In their work, the authors provide an overview of a number of teaching approaches that focus on the topic of AI literacy. They systematically investigate the methods used to teach and summarize what pre-requisite knowledge is expected of students that engage with the given material. They conclude that only recently, the material has shifted to a focus on beginners and that for most materials, knowledge in programming is needed, but that there are approaches which teach AI concepts more generally.

2.2.3 Gamifying AI Literacy

Using game-based elements to teach or apply AI is quite common in the AI teaching literature [Ala22; ZCC+21]. In the following, we want to look at a few of the concepts that can be found.

The KI Campus, as introduced in [RBM22], provides an online platform giving access to many courses in the field of AI. In comparison to the course described above, this approach uses the self-learning potential of practitioners, meaning that they do not give one dedicated course but many different self-contained modules. However, they do not provide a guiding path for learning and assume that interest in the single modules as well as the learning progress is driven by the user. As a consequence of the modular structure, the content and design of the different courses are dependent on the lecturer. Some of the listed modules on the KI Campus include gamification, but these are limited to only selected courses and chapters. This lack of an overarching thread is something that we want to improve upon in this work while also focusing deeper on gamification. This approach is similar to the popular courses on e.g. Coursera or Udemy, Brilliant. One game from this work, however, was an inspiration for our gradient descent game, as stated below. In this game, the player learns of the utility that a gradient provides in the search for the minimum of a loss function.

In a open guidebook[1] Black et al. describe a project-based approach to foster AI-Literacy in elementary school classrooms. They include detailed projects and guidelines for teachers in their work, which illustrate the concepts of AI through hands-on projects, sometimes using games like e.g. Tic-Tac-Toe.

Believing that games motivate students, the authors of ref. [MTR11] introduce a Java graphical gaming framework for an introductory AI course on an undergraduate/graduate level. Though not explicitly stated, the authors imply that students already possess programming experience. The envisioned usage of the game spans one semester, covering topics from ref.[RN09]. In their work, the authors introduce a programming framework, that spans programming intelligent agents in a variety of games The goals of the concept include learning how to choose an AI technique for a problem and discuss choice, implementing an AI solution for a real-world problem and analysing

[1] https://cdn.iste.org/www-root/Libraries/Documents%20%26%20Files/Artificial%20Intelligence/AIGDK5_1120.pdf

solutions, gaining confidence in the skills of a computer scientist, as well as to learn teamwork in programming. The authors argue, that students program a game/elements of a game rather than playing to learn.

Voulgari et al.[VZS+21] designed an educational game—the "ArtBot"—as supporting material for AI and ML education aimed at younger students. Their research aims to enhance the learning of fundamental concepts in machine learning, such as supervised and reinforcement learning. They created the game with the intention of stimulating students' critical thinking about the various factors and biases that can shape AI agents and systems. In the game, players are presented with the task of locating and retrieving valuable art objects that have been stolen and concealed. The first part of the game introduces the process of supervised learning, wherein players train their AI assistant to recognise specific art objects (paintings and sculptures). They then label a set of training data, experiment with different parameters, and assess the effectiveness of the assistant by observing how it categorises a set of testing data. In the second part, players and their AI assistants must navigate through a series of dungeons and retrieve the stolen art objects. The players are introduced to the concepts of reinforcement learning, where they guide their assistant by specifying what type of objects to search for and which ones to avoid (such as traps), and by assigning rewards to the correct objects.

The authors of [GVP+20] researched works that include games to teach topics of AI and ML. The objective of their study is to provide a comprehensive overview of the current research on games designed to facilitate AI and ML education. The authors examine the ways in which various games offer opportunities to teach AI and ML concepts and themes. They conduct a comparative analysis of seven games that target AI/ML subject matter for a pre-college audience. One of the games that they reviewed and that we viewed as interesting for our research is the game "Bug Brain"[2]. In this game the player has to design neural networks, using a simple drag-and-drop approach that performs certain types of logic functions. One interesting aspect of this approach is the fact that the exercises and high-level theory are described in a "book", i.e. a guide that the player can access at any time.

Overall, our findings of this literature search show that most game-based AI education frameworks focus on programming and decision-making, in parallel to what we found above, they often used block-based programming. On the other hand, the game-based NN education literature contains games which focus on applying NN to games or to playfully solve problems. This approach goes into what we envision, however, almost all games that we surveyed lack an explanation of the theory behind NNs. Those approaches (see for instance the bug brain game described above) that specifically included descriptions of the theory in them include this description only in text form, i.e. the theory is not incorporated into the game.

Quite a number of papers also focus on the training of NNs in order for them to perform a game. While this is different from what we aim to implement in our concept and thus not described in detail here, we also want to briefly mention this approach here, because it is a gamified approach in some sense. Again, however, it is not suited to teach the basics of e.g. backpropagation and requires existing knowledge. Although it is possible to gain this understanding by programming game agents to play a game, such methods assume that the person has at least a basic understanding

[2] http://www.biologic.com.au/bugbrain/

of programming (if block-based programming languages are used) or, at most, require strong programming skills. This can affect the accessibility of an educational approach. Since our goal is to make the entry point as simple as possible, we avoid using such an approach.

2.3 Findings Literature

Having identified a list of requirements which were informed by the results of our survey (see Chapter 3), we now turn to the literature. We searched specifically for the requirements or adjacent fields in research works, in the hope that we can identify works which can help our implementation or that may inform further ideas. These findings will then in combination with the results of our study be used to formulate concrete principles and competencies for our didactic concept.

To that end, we performed an exploratory review of our related work regarding learning goals and design principles. We identify key components and competencies relevant to our target group and goals. As the AI-Literacy frameworks focus on a high-level view of AI education (high level), they are a good resource for the study of requirements, as well as research works detailing the implementation of AI Curricula. Furthermore, we note that most research works only present a teaching framework and never explicitly spell out the competencies that they want to convey.

One of the frameworks that we looked at, identified three major dimensions, cognitive, affective and sociocultural [KZ21] as a broad categorisation that one might use for the competencies. These thoughts are mirrored in almost all research works surveyed for this section, such that we feel comfortable discussing only those three dimensions here.

In[LM20], these broad three categories are presented in the form of questions, which to us, seems very useful in the development of new competencies, as they help guide the design of a teaching concept for a specified target group.

For our target group, the questions focusing on the capabilities of AI, ie. the cognitive dimension seem to be the most relevant. The other dimensions are also important for PhD students, however, the goal of using NN in the research of PhD does not require a strong learning schedule dealing with the ethical (sociocultural) question, they are rather to be mentioned while learning on the side.The affective dimension, which deals with how well the students feel about their ability to enrich their abilities with AI (and NN, specifically) is also indirectly touched upon by our plan to use a game which hopefully motivates students to feel well in their ability to actually apply AI. As such, we also do not explicitly look at the affective dimension of our competencies.

Hence, it can be said that with respect to developing competencies in our targeted use case, one should focus on the cognitive dimension. Summarising, we want to provide answers to the cognitive dimension of our competencies. This includes in our estimation the questions: “What is AI?” and “What can AI do?” [KZ21; LM20]. Furthermore, we also want to touch upon ethical questions in our competencies, which includes the questions of “How can AI be ethically used in research?”.

Having mentioned very broad categorisations of competencies that are inspired by research works, we now want to go into more detail on actual research findings regarding important competencies that researchers found important in the field of AI.

As the work of Long et al. [LM20] is targeted at K12 education and below, the AI-literacy frameworks targets a broad range of educational levels from Kindergarten to High school. This, however, means, that the competencies and design guidelines of the framework have been designed with children in mind. Obviously, the level of cognitive ability expected from PhD students differs from those of a child, they focus much more on the need to develop abilities like critical thinking and ethical discussion. We assume that most PhD students already possess most of these competencies. Furthermore, the learning that happens in schools takes place in a very different environment and hence the principles around teaching and competencies are also slightly different. For instance, the tasks "Programmability: Understand that agents are programmable" or the design principles: "Support for parents" or "Critical Thinking" will certainly not have to be taught to PhD students.

Additionally, Long and Magerko's work defines competencies geared towards understanding the complete field of AI, rather than the sub-field of NNs. Given our goal of achieving NN literacy, we are not interested in the more general competencies. An example for competencies discussed by Long and Magerko is for instance one labelled "Sensors", a topic which is too broad for NN-specific content. The competencies that we judged as important for our work are summarised in table Table 2.1.

In the research work by Clarke et al. [Cla19], the authors published a concrete teaching plan tailored towards high school and undergraduate university students. Due to this detailed teaching plan, the authors provide more explicitly stated competencies. While they consider the tertiary level of education, they do not go into the deep theoretical foundations of AI, but rather look at the conceptual perspective on AI. Given that this is very close to our target group, as well as close to the level of explanation that we want to provide—the only difference is our focus on NN—we find this work to be very useful.

Omitting parts of the educational material that were deemed too broad in the context of NNs, we identified the following competencies as important for our work:

- Explain key terminology associated with the field of AI.
- Gain an understanding of how a neural network functions.
- Build, train, and test an AI system—gaining an understanding of data sets. Explain key terminology associated with the field of AI.
- Consider algorithmic bias and the effect of bias on individuals and society.

The authors of ref. [KSHH16] approach the topic from a more formal view. As described in Section 2.1, their defined competencies and educational goals focus on a theoretical background by teaching concrete, computer science-based topics, such as automatons or data structures etc. Only one of these classical computer science competencies deals specifically with ML. However, as we strive to equip PhD students with the scientific tools to work with NNs, we deem some knowledge in a formal approach to NN necessary. However, we agree more with the statement of Kong et al. [KZ21], who argue that beginner-level AI literacy programmes should focus more on conceptual understanding rather than emphasising mathematical formulae and programming codes. This seems especially relevant, considering the wide array of fields of study that the PhD students that we target come from.

In their work, Evangelista et al.[EBB18] provide another teaching concept that starts at a more formal level. However, their focus on mathematics is not as rigorous as the previous work. Instead, they focus slightly more on competencies dealing with the understanding that machine learning is about pattern recognition, algorithms and statistics. One of the key concepts that they want to get across deals with the way that pattern recognition can lead to solving segmentation problems.

A different type of approach that is followed by the authors of ref.[VZS+21],aims at teaching their students the process of supervised learning, teaching them the competencies of data sets, testing, classification problems, image recognition and the understanding of decision trees.

Competencies from Literature	Reference
Discuss the AI technique best-suited for a novel problem/domain Understand what "intelligence" means and that it is based on data Understand that ML is about pattern recognition	C2, C5 [LM20] [MTR11] [EBB18]
Understand structures and basic terms of a NN	C9 [LM20] [KCZ23]
Gain an understanding of how a neural network functions Build and Train a NN	[Cla19] [MTR11] [LM20]
Understand basic data literacy concepts Critically interpret results Describe how to input data can affect the results of an algorithm. Understand differences in learning techniques (supervised, unsupervised) consider algorithmic bias and the effect of bias on individuals and society	[VZS+21] [KCZ23] C11-C13 [LM20]
Build a solid theoretical foundation Make students understand that ML mathematics, algorithms and statistics	[SKGW21] [EBB18] [KSHH16]

Table 2.1: Competencies in literature considered in our didactic concept.

Finally, we also want to very briefly discuss design principles that can be found in the literature and which are interesting in our context. Most of the research works (as was already discussed above), have a different type of teaching in mind, i.e. focusing on classroom teaching or virtual lectures, where the design principles are clearly not directly applicable to our game-based learning concept.

In the paper AI atlas [SKGW21], the authors provide a good design principle of "canonization". Despite the fact that their work is intended to be used in a classroom setting, this principle of defining a chain of topics on which one focuses is directly related to our discussion (see Chapter 3) of the need to structure the teaching into a chain of lessons which build on another. Furthermore, in this paper, they made a key component of their design the intrinsic motivation of students and had a particular emphasis on letting students do exercises on their own, which again mirrors our design principles listed above.

Drake et al. [DTS15] focus specifically on design principles which aid in increasing the motivation of a student. They conclude that an approach, which investigates design principles for online learning has to be accessible, engaging and measurable in order to be motivating.

3 An Initial Requirement Elicitation

To uncover the expectations of PhD students towards a didactic concept, we conducted a survey in a pool of PhD students. One goal of this survey is to explore what design elements are needed in a didactic concept to keep learners motivated and engaged and what content do they need to learn. Another goal is to gain a first impression of how our target group could envision themselves being educated with game-based learning.

With these goals in mind, we created a questionnaire consisting of a set of open and closed questions and attached it in Appendix A.1. As summarised in Table 3.1, our questionnaire is structured into three main sections: The first section is about investigating the existing knowledge about NN and topics/competencies the participants need to understand. The second part of the questionnaire includes questions about the learning behaviour of the participants and it explores design factors of a learning unit that can enhance motivation to learn. This part also includes some specific questions targeting the usage of games and gamification in education. The third section covers questions about the demographic information of the PhD student.

To ensure the quality of answers, we distributed questionnaires to PhD students or Master students that think about doing a PhD in our environment. However, this resulted in a limited amount of participants and a fairly small variety of different research fields. This is why we also published the questionnaire online on a survey platform, again addressing Master and PhD students. This way, we hoped to increase the number of different views and to extend our findings.

Part	Goal	Exemplary Questions
1	Asses knowledge Requirements regarding content	What is your experience with NN? Define structures and the term NN. Where do you experience problems when learning about NN? For what do you need a NN in your research
2	Identify motivational factors Requirements regarding design factors	What disturbs learning? What motivates learning? How dos a good lecture look like ? How could a game motivate you?
3	Overview Demographics	What is your gender? What is the field of study you do your PhD/Masters in?

Table 3.1: Structure and intention of the questionnaire for the initial requirement elicitation.

Academic Background	Number (percent)	Academic Background	Number (percent)
Business and Economics	6 (22,22%)	Medicine/Biology	2 (7,41%)
Computer and Information Technology	5 (18,52%)	Physics	2 (7,41%)
Psychology	4 (14,81%)	Educational Science	1 (3,7%)
Engineering	2 (7,41%)	Hospitality	1 (%)
Mathematics	2 (7,41%)	Media and Communication	1 (3,7%)
Total Participants: 27 (100%), 1 answer (3,7%) was not classifiable			

Table 3.2: Academic background of the survey's participants.

We did not exclude PhD students based on their knowledge, with the reasoning, that more experienced PhD students can better specify problems and needs while learning about NN and can already address where they struggled. This provides valuable insights also for beginners, informing us what it is that beginners should learn to function on the level of more seasoned students. This is especially true because beginners can not really express what they want to learn, considering that, by definition, they have not learned those parts yet.

3.1 Demographic Data

Over both groups (the public and the private) combined a total of $n = 28$ people participated in the survey. One answer, however, was not considered useful so we only considered 27 as the number of participants. Out of the participants, 14 were female, 12 were male and 1 person decided not to specify their gender. As stated above we decided to include master students in our target group. While participants studied a variety of fields as shown in table Table 3.2, there was a noticeable trend of PhD students towards STEM fields.This slight bias must be kept in mind when interpreting their answers.

3.2 Identifying Requirements towards the Content

This section focuses on the analysis of the survey results. The results of content-related questions in the first part of the questionnaire are used to identify what competencies and skills the learning concept should cover. The results of the learning behaviour questions are used to define the requirements for the design of the learning concept.

As shown in Figure 3.1 most of the participants are fairly inexperienced with the topic of NN. They were asked to rate their experience on an ordinal scale from one to five, where one represents that participants never had come into any contact with NN/only have heard the term NN, and five represents them being experienced in the topic. As shown in **??**, the majority of students rated their experience with two or fewer. Hence, our pool of participants contained quite a number of inexperienced users, but also ones that were already very familiar with the matter.This results in an

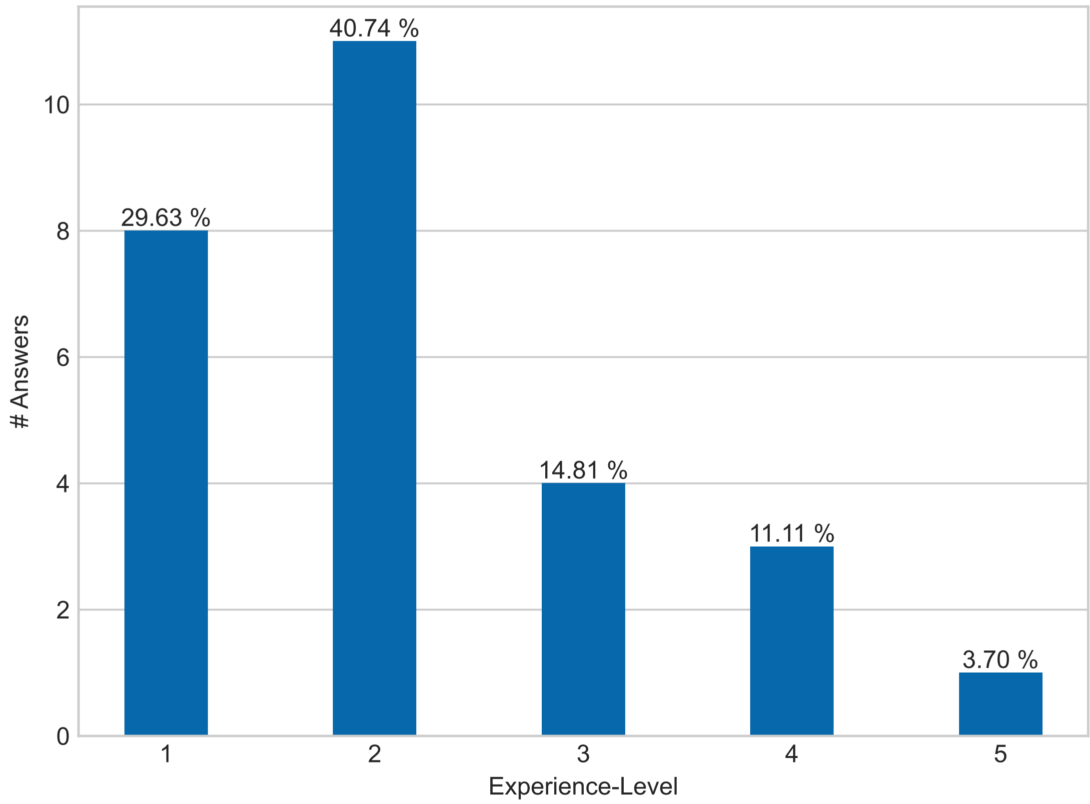

Figure 3.1: Self-assessed experience level of the study's participants. 1 means "not experience", 5 represents "very experienced".

average experience of 2.2. Furthermore, this indicates, that while there are students that possess deep knowledge in the field of NN at the time they are starting their PhD, they generally seem to be the minority.

Our findings suggest, that the usage of NN in research for PhD thesis often includes the usage of an existing NN, i.e. the application of this preexisting NN to a research problem. Methodologically, this usage of an existing NN entails either changing code or adapting hyperparameters of NN to adapt them to a given goal. Out of the participants,48, 1% stated this adaption of existing as the potential type of usage of NN in their research. 29, 6% specified 3,7% (1 Person) Did not know how to use for a task/problem in their research

In summary, this suggests that defining/programming a NN model from scratch is only important for special cases, where no existing research in related fields can be re-used. It is much more common to adapt and modify an existing NN from a related field that can be found in the literature. Hence, it is mostly interesting for PhD students to be able to understand these already defined models and to understand how they might adapt it to increase their usefulness in their own research.

Having looked at the typical way that students look at NNs in the context of their research, we want to briefly touch upon what exactly their level of knowledge looks like. When we consider the amount of inexperienced participants, a surprisingly large part of 41% considered a NN as a

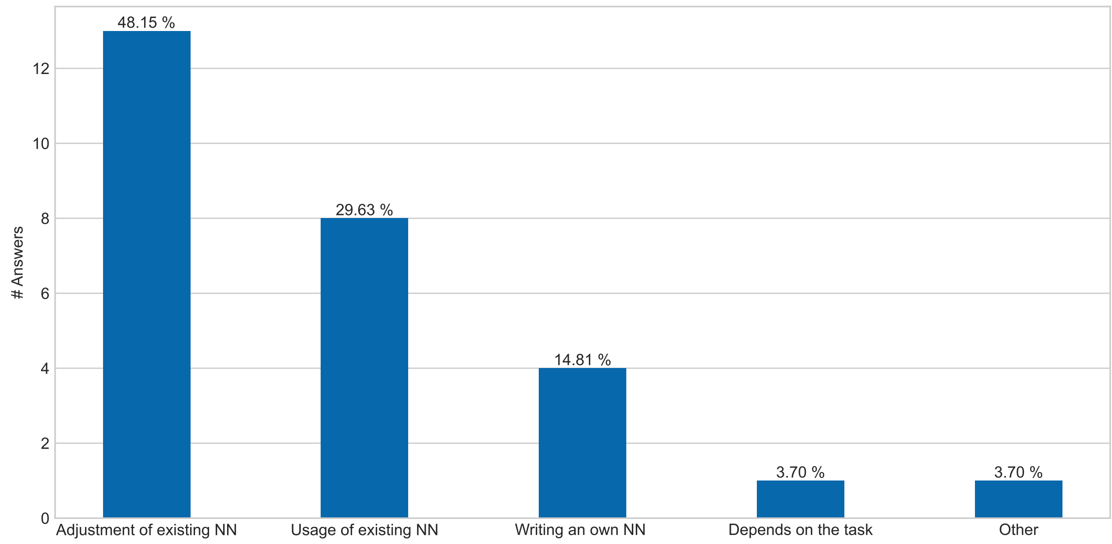

Figure 3.2: Type of application of NN in the student's research.

mathematical function when asked of their intuition of a NN. In contrast, only 22% understood NN to be—as the popular image holds—an artificial replica of a biological brain. One person described NNs as decision-making using training data and adjusting the decision-making in the process of learning. This fairly surprising perspective on NNs might be influenced by the dominant STEM background of participants. Nevertheless, the results hint that including a formal approach to NN in our didactic concept should be considered.

We asked participants to define the term NN as well as to explain the structural parts of a NN in order to gain an understanding of the depth of the student's knowledge level. As expected, those who considered themselves experienced or very experienced, could give a rather detailed definition of the asked terms and showed understanding of the relations between the terms as well as the formal foundations of a NN. In contrast, beginners often could either give only an intuitive definition of the terms or none at all. As expected, generally speaking, the lower they estimated their own experience with NN, the less precise and more intuitive their definitions became. This trend extends to their knowledge and understanding of the relation between all the terms that we considered.

Overall, we interpret these results as the following: The fundamental terms and concepts that are commonly used in the field of NN should be defined precisely and explained thoroughly for beginners. Given that none of the experienced users had any problems understanding the terms and their relations with one another, we conclude that this knowledge likely is very important to be able to use NNs. The importance of understanding the fundamental terms is further highlighted when we consider the results of the previous section, as one has to understand the working parts of NNs in order to be able to navigate the research field, enabling one to re-use existing models.

In accordance with the participant's broad field of experience, the problems they struggled with were equally broad—from complex problems to basic ones. Experienced participants (experience level of four or five) started to stumble upon problems with the optimisation of implementation and reported confusion about the connection between different NN concepts. I.e. they wanted to broaden their horizon of knowledge about NNs and optimise what they had learned.

Participants with experience rated as three struggled to find a platform that combines mathematics and intuition. They also experienced problems with the implementation of the concepts that they know about theoretically.

Those with little experience (experience level two or less) described confusion and exhaustion when learning about terms and relations in a NN. They reported that the number of terms used in the context of NN was too numerous and that they struggled to understand the relation between the terms. Furthermore, some stated that they had difficulties with the mathematical formalisation of NN.

These difficulties in the understanding of beginners were further worsened by the lack of understanding of how to solve problems with a NN. Specifically, with how NN can be applied to real-world problems. Also, this includes the question of when to use NN and which particular solution should be used, what strategies of implementation to use etc.Again, participants with no experience lacked the means to express their problems. Overall, they also reported problems in imagining what exactly constitutes a NN and what, broadly speaking belongs to the concept of NNs, i.e. they reported a lack of overview. They had problems finding the right medium and platform to learn about NNs and to find an entry point into the space, which lead to them reporting that they sometimes felt lost and scared. Consequently, it seems important to provide beginners and participants with little experience with a clear, guided way to allow them to familiarise themselves with the topic of NN.

Participants further struggled to understand NN due to their lack of knowledge on how to solve problems using this technology, particularly in real-world applications. They faced difficulties in deciding when and which specific NN solution to use, as well as how to implement strategies effectively. Again, participants with no experience lacked the means to express their problems, while also experiencing issues in grasping the concept and scope of NNs. They had trouble finding appropriate learning resources and entry points, leading to feelings of confusion and intimidation.

Based on their answers, the following points need to be addressed by the content and competencies in our didactic concept:

- Address need for formal knowledge
- Cover basic terminology and the related structures in an understandable manner
- Explain conceptually how an NN works
- Need for low entry point; make content accessible to people with no programming/maths skills

Essentially, it is crucial to provide a well-structured and guided approach to enable beginners and those with little experience to become familiar with NN.

3.3 Requirements towards the Design of the Concept

In this part, we aim to identify and define the learning behaviour of the participants and their idea of a successful learning experience. Additionally identifying their requirements towards the design of a successful learning tool.The results of these questions will later be used to define what design considerations should be incorporated in our concept to facilitate learning and thus engage and motivate students. When teaching a topic, it was often mentioned that it is best to slowly

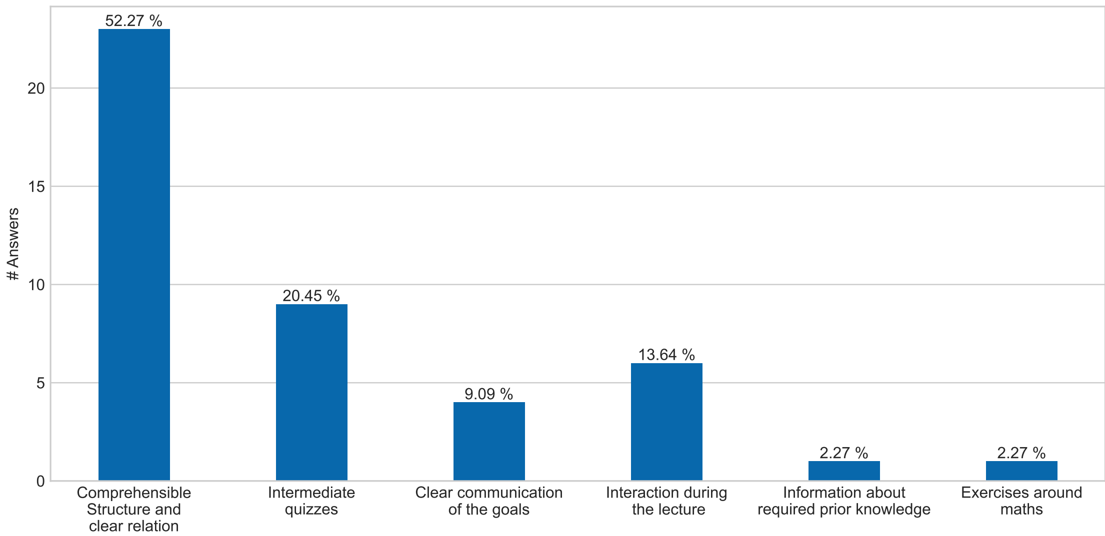

Figure 3.3: Preferred methods of information communication.

unveil complexity by first describing high-level topics and leaving details be. Out of our survey participants, 70% answered that they preferred a top-down approach, where on gets the general context and high-level goal first. The other participants reported that they preferred tackling new concepts bottom-up, meaning that they like to first understand the details first before building a bigger picture. Interestingly, all PhD students that participated, said that they preferred the top-down approach.

We asked what they need to learn in three dimensions: The first dimension was in relation to how information should be communicated in a lecture. The second, is what didactic concepts students need to retrieve information. And thirdly, which methods do they prefer when learning on their own or repeating content?

When asked about how they preferred a way to communicate new information, students emphasised the importance of clear and structured content in a didactic concept. In a multiple-choice question, 23 out of 27 participants indicated that a comprehensible and cohesive structure, as well as clear relations between different topics within a subject, are important for a good lecture. **??** shows, that additionally intermediate quizzes to assess knowledge and learning progress were also considered important, receiving nine responses. Two new options were added to the list of preferences: one student felt that exercises for mathematical concepts were important, while another declared statements about essential prior knowledge as to be helpful.

Our survey findings indicate that in order to effectively learn during a lecture, it is crucial to have practical examples that illustrate the implementation and application of the content, as shown in Figure 3.4 This was identified as essential by 12 participants of the respondents. Additionally, interactive methods of delivering the content were also deemed important by a significant portion of students, as shown below in the figure. This includes techniques such as questioning and discussion. Participants judged as almost equally important the use of graphic representations and colour highlighting to supplement the content.

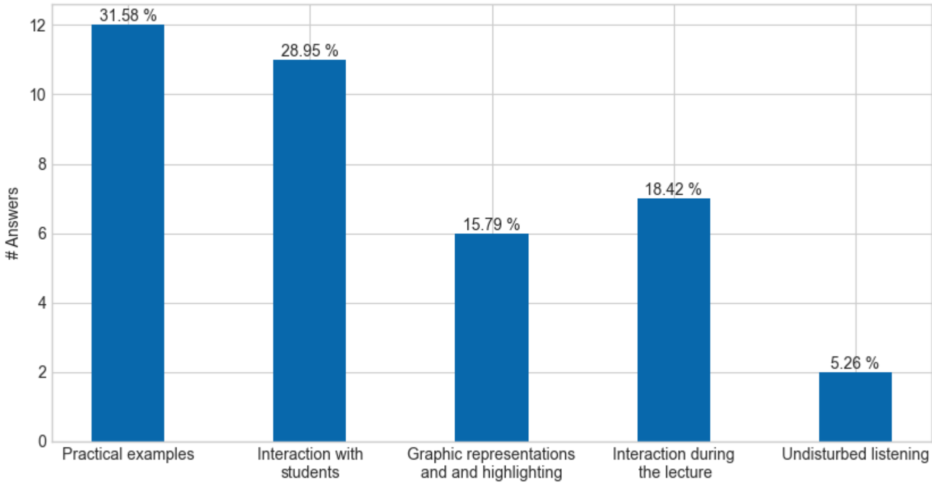

Figure 3.4: Preferences for retrieving information during a lecture.

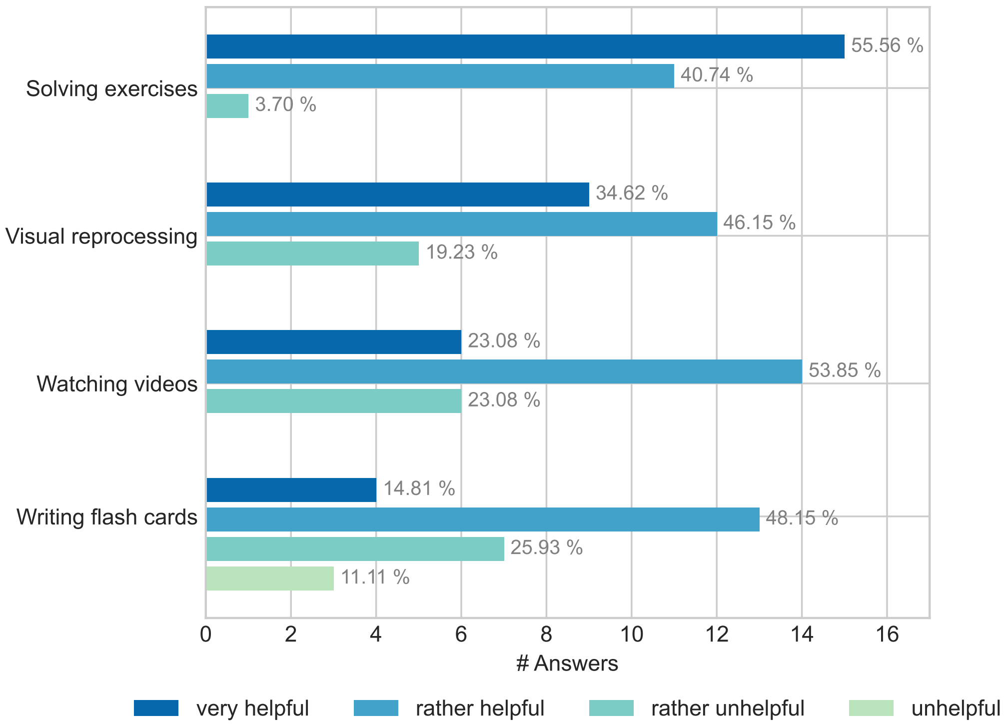

Figure 3.5: Perceived helpfulness of methods for deepening knowledge

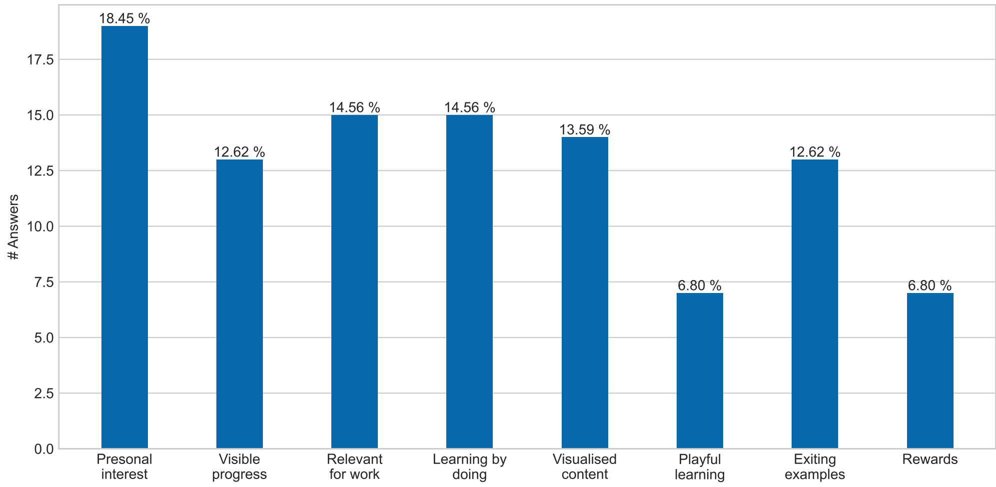

Figure 3.6: Factors that promote student's motivation

Regarding the preferences on their own learning behaviour, the results of our study presented in Figure 3.5 show that almost all participants deemed solving exercises and problems a very or rather helpful, making this an important focal point.

Students rated the methods "watching videos and visually reprocessing information" almost equally important with a slight preference toward the visual reprocessing of topic e.g. in form of creating mind maps about the content. While using flashcards in comparison was considered to be the least helpful method, a significant amount considered writing down content on flashcards as helpful. These answers show, that learning a new topic not only one way but a synthesis of different approaches is helpful.

As the results of the questions above suggest, there are vast differences in how students process new knowledge as well as in how they prefer to engage with the material in order to learn new things. This affects three stages of learning, namely how the information is first communicated, then how and in what form they receive information and lastly how they deepen this knowledge.

In that regard, for the communication of learning material, it was deemed most important to present it in a structured way. In order to receive the information in an efficient way, they mentioned that they want practical examples and in order to deepen their knowledge in self-study, they mentioned their preference for exercises and study problems that they can solve. Mind maps and watching videos were also mentioned in the context of self-study.

From this we conclude that we do not want to offer only a single way of presenting and communicating material in order to accommodate the mixed learning types of students.

In Figure 3.6 we summarise the result of our survey regarding the aspects that motivate students while learning. Broadly speaking, almost all options that were offered were also considered to be motivating to students. The majority reported that they were motivated to learn, if they are interested in a topic and similarly if it is applicable to their work. They also reported that they are motivated by being able to experiment and if the learning progress is clearly visible to them. It seems fair to summarise the main take-away of this question to be that intrinsic motivation is consistently judged as very important in motivating students while learning.

After gathering responses on factors that contribute to participants' motivation, we identified the following components: Consistent success was a significant influence on participants' motivation. Participants described the feeling of comprehension and coherence as an ünderstanding and making senseßensation. Participants feel successful when they overcome challenges, solve difficult problems, and acquire new knowledge. Having the means to surpass areas where they are stuck also increases their motivation. The existence of objectives was closely linked to the sense of accomplishment. Participants were motivated by reflecting on their objectives, establishing and achieving them, as well as receiving progress feedback. However, the goals do not have to be major to inspire participants. Small goals, or "taking one step at a time,"can provide a continuous sense of accomplishment. One participant liked to reward themselves after completing a goal. The participants were highly motivated by practical illustrations demonstrating the applicability of the content to their work or daily lives. Having these connections to the "real worldïncreased their understanding of the content's relevance for themselves and motivated them to learn.

Our findings also shed light on what disturbs a student's learning process. It was mentioned that the lack of feeling of success while learning, as well as the feeling of missing the relevance of what one learns is detrimental to the motivation of students. This also includes the feeling that the material lacks relation to real-life problems. Unsurprisingly, students felt as especially de-motivated and frustrated by the feeling of being stuck too often.

Further negative influences on learning behaviour were various activities such as social media, friends and hobbies that appear more enjoyable or are given higher priority, which can distract students from the learning material. Other environmental factors that compete with the students' attention were listed as noise and other deadlines. Additionally, overly complex content, a lack of understanding of the big picture, or too much information given in a short amount of time can hinder learning. Students also reported that lectures lacking structure, jumping around topics without clarifying relationships and using "boring" and unengaging teaching methods can decrease motivation to learn. Finally, unclear entry points into topics or an excessively high level of entry, requiring too much prior knowledge or skills, can cause frustration and impede learning.

In order to maximise a student's focus and concentration on learning, it should be avoided to include too much complexity in a given lesson, which includes making the introduction to a new topic as easy as possible. Furthermore, it should be clearly communicated how the knowledge that is communicated furthers the students goal, and we aim to make the teaching methods varied, in order to keep teaching interesting.

Summarising motivational and disturbing factors the following can be derived for a didactic concept:

- The concept should foster a sense of accomplishment and success for learners.
- It should provide goals and opportunities for continuous progress, and offer support to avoid getting stuck.
- The complexity of the subject matter should be broken down into self-contained small units that are presented incrementally over time, with supplementary materials or follow-up units for additional understanding of the topic.
- The concept should emphasise the relevance and practical application of the knowledge to the real world.

- The learning process should be hands-on, with opportunities for learners to apply their knowledge to real-world problems.
- Fun and diverse learning also includes different learning methods.

We also asked questions aimed at understanding what factors motivate students with respect to game elements, i.e. what students imagine a game-based, motivating course to look like. It should be mentioned at this point, that one participant explicitly mentioned that he preferred to learn through a more classical setting. However, all of the other participants positively viewed the idea of learning through a game-based approach.

The following elements were mentioned as motivating and promoting learning: The use of quizzes challenges and quests in conjunction with an underlying storyline. Generally, rewards and visualisations of progress were mentioned as particularly motivating, which was verbalised as the ability to "level-up" one's character. This need for visualisation extends to the realm of visualising the concepts that one learns and they want to be able to directly interact with the content in some way. Furthermore, most mentioned that they would prefer to have a guide, as a way to lower the barrier to entry; one participant summarised the use of a guide as something that "holds your hand" while learning. Such a guide should break down the complex topics and ease the player slowly into understanding the complexity.

Interestingly, another element that was mentioned was the ability to compare oneself to other players, which even extends to challenging and competing with other students, as a way of increasing one's motivation. Another interesting aspect which was mentioned was to add the ability to extend what one learns in the game into the "real-life", for instance by allowing one to draw mind-maps, which then can be used in the student's projects, after having finished with the course material.

Overall, all of these answers that the students provided serve as input which informs and inspires our implementation of the concept, which will be presented in the following chapters of this work.

4 Introducing a Didactic Concept for Teaching the Fundamentals of Neural Networks to PhD Students

In this chapter, we develop a didactic concept for teaching the fundamentals of neural networks to PhD students who have little to no knowledge in this field, and who may potentially require neural networks for their research. Our approach incorporates the requirements and didactic design principles identified in Chapter 3 and outlined in previous works (see Section 2.3). The concept aims to reduce the barriers to entry for this target group by providing them with the necessary knowledge to effectively use and apply neural networks and facilitate further exploration of this topic. To make the concept accessible for a broad range of PhD students, we address concepts more conceptually [KCZ23]. We strive to make our teaching engaging and motivating by emphasising the enjoyment of learning as a central goal of our approach.

It is not our goal to teach detailed mathematical and computer scientific concepts, which are not directly required to successfully use and deploy NN models. Furthermore, there already exists a large volume of works already focused on teaching exactly these formal concepts (see for instance [KSHH16; SKGW21]).

We feel, that in creating such a more general, high-level concept, we add more value for PhD students, especially given that to the best of our knowledge, no such course exists yet.

With these goals in mind, we formulate competencies and design principles in the remainder of this chapter. Regarding the competencies, we look at existing literature on AI literacy, focusing on what researchers have identified as important. Once those important aspects are identified, we compare them and adapt them to our target group. For the design principles, in addition to the AI literacy literature, we aim to maximise the fun aspect of learning for students. Furthermore, based on findings in Section 3.2, we want to assume as little programming background as possible, as the requirement of knowing how to program excludes a number of students from participation [KCZ23; LM20].

These competencies are to be taught in the form of an educational game, where the previously identified design principles are to be implemented. Contrary to the work presented inSection 2.2, our educational concept is not designed as supplementary material for an AI lecture but rather be treated as a standalone self-learning tool. The choice for a game as the implementation of our concept will be elaborated on in the next chapter Chapter 5.

After introducing the general outline, goals and motivation of our didactic concept, we will now dive into the details by defining competencies and design principles in the following sections.

Lvl.	Taxonomy	Verbs
1	Remembering	know, define, list, recall
2	Understanding	identify, summarise , discuss, explain
3	Applying	apply, illustrate, demonstrate
4	Analysing	differentiate, compare, distinguish
5	Evaluating	judge, consider, argue, decide
6	Creating	compose, develop, formulate, create

Table 4.1: Overview over taxonomies for educational goals and verbs used to formulate them based on [WL16].

4.1 Formulating Competencies

By combining findings from the literature research and the findings from our survey, we formulated competencies that aim to cover both the theoretical foundations as well as the requirements from our target group.

For our didactic concept, we define *competencies* based on Schwippert et al. [Sch01]. They specify competencies as the cognitive abilities and skills that individuals possess or can acquire to solve specific problems, including the capacity to apply problem-solving skills effectively in various contexts. We express competencies by formulating them as specific learning goals, which we use interchangeably with the terms educational goals or teaching goals. In this context, each learning goal corresponds to a particular capability or skill.

To differentiate the cognitive complexity of the educational goals for our concept, we use Andersson and Krathwohl's [AKB00] taxonomy in combination with Bloom's verbs [BEF+56], which were designed for this exact purpose. Table 4.1 outlines the taxonomy levels with an extract of their corresponding taxonomy verbs. The verbs that were used in the context of this work are highlighted in bold.

Given the constraints of our target group and the goals that we want to pursue with our concept, the competencies mainly gather around the cognitive dimension of AI literacy, paying attention to the sociocultural and affective dimensions if needed. In the following, we describe five competencies that we identified as key to our concept.

Competency 1: NN Strengths and Weaknesses This competency is based on C2 and C5 of the AI literacy framework by [LM20]. Broadly speaking, it deals with intelligence and the strength and weaknesses in AI. However, in our case, we only interpret this to deal with NNs. Thus, this competency aims at providing students with the required skills to understand what intelligence means in relation to NNs and how to evaluate how this intelligence is obtained during training. This competency might also be summarised with the short: "What makes a NN intelligent?"question. In the context of a NN, it is crucial to understand, that pattern recognition is one of the key factors when discussing intelligence [EBB18].

Also interesting for this competency are the results of our survey, where students reported problems with grasping the context of the origin of this intelligence and precisely stating what a NN is. Usually, they reported problems in having a clear overview of what types of methods and problems exist, which are categorised under the term NN. Consequently, students need to know not only the topic of NN but understand roughly other types of methods in order to correctly estimate the place that NN hold in the broad field of AI.

Furthermore, this includes the understanding and ability to critically evaluate what types of problems NNs might be applied to. This contains the question of the more subtle choice of the right type of NN suited for a particular problem, for which students have to be familiar with the taxonomy of different NN types. I.e. this competency should also enable students to answer why NNs are an appropriate choice for their research problem/field [MTR11].

In order to reach the above competency, we can identify the following sub-goals

Learning Goal 1.1 Classify NN within the field of AI.

Learning Goal 1.2 Discuss intelligence in the context of NN

Learning Goal 1.3 Argue for what problems the usage of NN is suitable and for what not

Learning Goal 1.4 Identify challenges for NN

Competency2: NN Structures With this competency, we aim to create in students an understanding of the fundamental structure of a NN. It focuses on the understanding of the static components of a NN as introduced inSection 2.1.1 Similar to C9 of the AI literacy framework, which encompasses the understanding of steps involved in ML, we focus on introducing the "structural" components involved of in NN [LM20]. We identified with our study—in combination with [**russel10a**] and [KCZ23]—as important structures: neuron, links, weight, bias, the concept of activation, the concept of feedforward and activation function input, output and hidden layer. As seen in the work of [LM20] we additionally include what steps are needed to learn. Since most of the inexperienced participants could not give a definition of the fundamental components of a NN, this seems to be a very important competency for us to teach. This also involves understanding the function of the structural components and their interaction, as our study showed that students struggle to keep up with the different components and their relations, as well as how exactly they work together.

Learning Goal 2.1 Define *artificial neural network* in your own words.

Learning Goal 2.2 Know the structural components and basic terminology of a neural network

Learning Goal 2.3 Explain the function and relation of the structural components in a NN

Learning Goal 2.4 Discuss how changes in a structural element impact the other components

Learning Goal 2.4 Analyse the steps involved in the result of NN(Build, Train, Apply)

C1: NN Strength and Weaknesses Understand NN in the context of AI. Understand *intelligence* in the context of NN and discuss problems a NN is suitable for. **References:** [EBB18; LM20; MTR11]	**C2: NN Structures** Understand the structures of a NN and their relation. They know the phases involved in decision-making (Build, Test, Train) **References:** [KCZ23; LM20; RN10]

Competency 3: NN Learning In contrast to Competency 2, this competency focuses on the dynamic mechanisms of a NN. In particular, the aim is to explain and make accessible the process of learning in the context of NN.

This might be formulated in other words to state the goal is to "gain understanding how NN function" [Cla19; LM20]. In our study, participants that were slightly more experienced, but not yet operating at an "expert level", expressed their struggle with "intuitively understanding", how the learning process of NNs looks like and how it works in detail. While the participants, which were at a beginner level could not articulate their problems as specifically as more experienced interviewees, they also largely reported confusion with the understanding of the learning procedure. Taking these findings, the goal of this competency is to enrich users with the skill of a better understanding of the learning dynamics of NNs. This includes the understanding of the basics of gradient descent optimisation, cost functions and backpropagation and familiarising students with algorithmic thinking in this context.

This competency is not about achieving a mathematical, in-depth and very detailed level of understanding all the involved algorithms. Rather, it aims to equip students with a high-level understanding of the important concepts of learning.

Note that given the current state of the research regarding the explainability of NNs, it is currently not possible to describe in detail how a NN comes to a specific decision [**zednik21**]. The understanding, that how NN come to a decision is currently opaque is included in this competency, as it has real-world implications for the usage of NN. From all of the above, we derive the following educational goals:

Goal 3.1 Conceptually explain core mechanisms involved in learning such as *gradient descent* and *backpropagation*

Goal 3.2 Describe the process and goal of learning

Goal 3.3 Analyse what parameters influence the output of a neural network

Goal 3.4 Discuss pitfalls in learning such *local minima* and *learning rate*

Goal 3.5 Understand intuition of cost function

Competency 4: The Role of Data Understanding the importance of data for the outcome of a NN is essential for students that only want to use a NN for their work but also for students, that need to understand NN in detail for their PhD thesis. Thus, we integrate the core statement C12 of the AI literacy framework into our competency, emphasising that data are essential for NN. [LM20].

When working with data it is important to understand data sets. The ability to effectively work with data is called data literacy [PM13]. To acknowledge the need for this ability, we also adapt C11 of the AI literacy framework, which is centred around the understanding of data [LM20]. In our concept, we focus on problem-related interpreting of data. Our objective is to equip students with the ability to differentiate between data sets and assess their suitability for a specific problem and create awareness, that not only data but also their label are crucial for the result of NN.

In order to achieve this goal, students must possess knowledge of the relevant terminology and understand how these elements impact the behaviour of a NN. As demonstrated by the authors of [VZS+21], this includes familiarising oneself with training and testing data sets, classification, labelling, and prediction accuracy. Based on their work, we integrate the understanding of supervised and unsupervised learning and the differentiation between those learning algorithms into our concept to meet the expectation of our target group.

Moreover, students must acknowledge the ethical implications that arise when using real-world data sets in an opaque system. As illustrated C13 of the AI literacy framework [LM20] as well as in [KCZ23], students should recognise that data and the output of NN cannot be taken at face value and need interpretation. Additionally, they should describe how training data can influence the outcome of a NN. Our concept should provide the ability to Discuss the choice of labels and analyse the risks of labelled data and understand examples, where unsuitable data might cause problems in the real world.

To that end, we introduce the following learning goals:

Goal 4.1 Discuss differences between *training data*, *testing data* and *"real" data*.

Goal 4.2 Analyse how input data affects the results of a NN.

Goal 4.3 Critically interpret output of a NN.

Goal 4.4 Understand algorithmic bias and discuss ethical implications

Goal 4.5 Explain key-terminology in context of learning

Goal 4.6 Distinghish diffrent learning strategies from one another.

<table>
<tr>
<td>C3: NN Learning
Conceptually understand the dynamic mechanisms and algorithms involved in the learning of NN.

References: [Cla19; LM20]</td>
<td>C4: The Role of Data
Critically read and analyse data. Understand how the input data (training set) influences the output in a NN and what ethical implications may arise
References: [KCZ23; LM20; VZS+21]</td>
</tr>
</table>

Competency 5: Formalising NN During our research, two main positions seemed to be present: one may approach NNs in a formal way, such as [SKGW21] or ignore formal and rather approach conceptually e.g. [Cla19].

While the formal description of AI is not explicitly stated in the AI literacy framework [LM20], other approaches focus on the formal underpinnings of AI and ML. This they do by e.g. starting their teaching with courses on automatons and graphs [KSHH16; SKGW21]. We decided to design a competency on the formal understanding of NN, since it is deemed important for our target group of PhD students and as the importance of formalisation has also been acknowledged by other AI literacy frameworks.

One of the main reasons behind covering the basic formal concepts behind NN is to provide students with the knowledge to read scientific papers about NN. Almost all research works use mathematical notation to explain the NN architecture that they investigated, and hence students should be prepared and not feel insecure when interpreting these papers. By including this competency, we want to ensure that students are motivated and prepared to further expand their knowledge base after having participated in our course.

It is important to note, that the need to understand the underlying formal concept arose directly from our target group and their answers in the survey. Most of the participants in our survey stated that they might need to write—or at least understand code—in order to go from a conceptual level of NNs to using it in their project. Furthermore, participants of a medium experience level said that they struggle with the mathematical framework behind NNs. This tells us that for sustainable learning, one needs to have an intuitive understanding of mathematical concepts as well as be familiar with common notation.

Put into words, the goal behind this competency is to "make students understand that ML is about pattern recognition, mathematics, algorithms and statistics" [EBB18]. It is important for student to familiarise themselves with the formal notation of NN—especially with the perspective of needing to read and understand scientific work.

To that end, we introduce the following learning goals:

Goal 5.1 Know the formal representation of central structures and mechanisms such as neurons and activation.

Goal 5.2 Intuitively understand the mathematical foundations of a NN

Goal 5.3 Understand, that the goal of NN is the optimisation of a cost function.

C5: Formalising NN	**D1: Make Success Reachable**
Familiarise students with the formal approach toward structures and concepts of a NN **References:** [EBB18; KSHH16; SKGW21]	Ensure that students continuously progress and feel regular success moments. Make their progress visible. **References:** [SKGW21]

4.2 Defining Design Principles

Authors such as [LCL17] have shown, that motivation has a noticeably positive impact on the effectiveness of learning. They argue that when it comes to learning outcomes, a strong motivation to learn has a remarkable positive effect on the amount of knowledge gained [LCL17]. We found this to be true when considering the results of our initial research. As such we will formulate our design principles around motivating and engaging methods, as we hope to increase the students' interest to learn. In this following section, we establish a set of design principles for our didactic framework by modifying the principles found in existing literature and integrating these with the outcomes of our conducted survey.

4.2.1 Make success reachable

A range of our study's participants emphasised that experiencing a sense of progress in their learning significantly boosts their motivation to learn. Through summarising and analysing the students' statements, we determined that one of the prominent factors in maintaining motivation throughout their studies is the ability to observe learning progress and feel accomplished after completing a learning unit, as it brings them closer to their ultimate objective. This aligns with the principle of "Intrinsic Motivation" used by the authors of [SKGW21], who highlight the influence of the need for competence on behaviour and motivation. Drawing on the participants' responses, we have developed the following guidelines by breaking down this core principle: To create a sense of achievement and maintain interest and engagement, it is crucial to ensure continuous progress and regular moments of success. This can be achieved by breaking down larger goals into smaller sub-goals that are challenging but attainable within a reasonable time frame and level of complexity, generating frequent small successes that will keep learners motivated. Consequently, experiencing difficulty in comprehending topics or becoming stuck and not making progress can demotivate students from continuing to learn. Therefore, our concept should include a mechanism that assists and guides students when they encounter problems during the learning process.

It is crucial to note that it is evident how continuously achieving smaller goals will contribute to the overall progress towards the primary objective. In simpler terms, the study progress should be trackable. To that end, our study participants expressed the importance of having a visible progress tracker.

Additionally, participants reported that being rewarded for their progress during studying enhances their motivation and encourages them to tackle the next topic. Consequently, our pedagogical approach should incorporate visible rewards for learners upon achieving specific goals, not only related to learning but also, for instance, practice. We note that providing rewards for activities and visualising the progress can already be seen as gamification. In games, badges, collectables and achievements serve these functions.

We summarise all these requirements in the following list:

R1.1 The concept shall provide a visual representation of the student's learning progress

R1.2 The concept shall provide a reward for achieving goals or accomplishing a challenge

R1.3 Each learning unit shall be small enough to be completed in a short time

R1.4 Provide a feature to avoid getting stuck

4.2.2 People are different

When discussing this principle, we consider the design guiding *D9* of the AI literacy Framework, which is also addressed by the authors as they focus on how the cultural and ethical backgrounds of students might impact their perceptions about AI [LM20].

As our didactic approach is intended for university (PhD) students, we take into account their academic background instead. This included the various scenarios in which they might use a neural network and the diverse range of skills and prior knowledge that students have indicated in our study. Consequently, an important challenge arises, that lies in identifying the least common denominator while also considering the individual needs and discipline-specific requirements of each student. Despite breaking down our target group into beginners in the field of neural networks, we have observed through our initial study that there are varying levels of proficiency among this group. As evidenced by our study, some students already possess a background in mathematics or programming, others have been exposed to neural networks before, and some have no prior experience with either. Therefore, we acknowledge the need to offer students the flexibility to tailor their learning experience to their current and desired skill levels and to adapt the learning experience to their specific needs. Additionally, the content and skills taught should be adaptable to the student's individual needs. This follows the philosophy of adapting the content to students' needs instead of the other way around.

Students not only possess varying levels of knowledge, but they also have distinct approaches to receiving, processing, and communicating information as we investigated in our initial study. To address this, Fleming developed the VARK model, which categorises individuals into four learning types: Each of these types is defined as follows: The Visual Type prefers to learn through visual aids, such as graphs and charts, while the Aural Type prefers learning through spoken information and lectures. The Read/Write type learns best through reading and writing, while the Kinesthetic Type learns best through hands-on experiences and physical activities[FB19]. Our survey confirms this, as most students were found to have mixed learning styles, even though they may prefer one type of learning over another. Consequently, our didactic concept should incorporate multiple modes of presenting and interacting with the learning content to cater to different learning styles. Nonetheless, we have noted that when it comes to deepening their understanding, participants indicated that interactions, examples, and visualisations were the most crucial aspects.

In the end, it all comes down to knowing who your students are and what they need. This will ensure that the material is presented in a way that is accessible to all learner types, which in turn is expected to have a great influence on motivation. Thus, the above-described points lead to the following requirement list:

R2.1 Give the possibility to adjust the learning experience to the students existing/required skill set (e.g. A Basic Mode, a Programming Mode and a Mathematical Mode).

R2.2 Provide different ways of learning (e.g. different media, different ways of interaction).

D2: People are different	**D3: Structure ad Transparency**
Acknowledge the student's different skill levels and academic backgrounds as well as their different way to process information. **References:** [FB19; LM20]	Ensure that content is structured in a comprehensible way. Provide guidance by unveiling structure and learning goals **References:** [SRP05]

4.2.3 Structure and Transparency

Our study findings suggest that well-structured content and learning units, which step through the material in a sequential manner, facilitate the comprehension of complex subjects by exposing the relations and interdependencies through their organisation. Students stated that well-structured content which informs about topics and goals is important for their motivation and progress.

Summarising our participants' statements, this approach also enables learners to assess their current level of knowledge and determine the gaps in their understanding, as well as identify the topics that must be understood before proceeding to new ones.

The positive effect on motivation and learning efficiency is supported by the findings of Seidel et al. [SRP05].They showed, that coherently structured lessons, which are transparent about their structure and goals, have a positive effect on the student's interest and competence development. Brophy [Bro84] pointed out that goal clarity and coherence in the instructions are necessary conditions for students to be able to successfully learn concepts and that it is one of the main predictors of student success. Furthermore, a well-communicated structure, review of the objectives and outlines of the content have been identified with maximising the achievement of learning material.

All in all, we have the goal of making our concept provide a clear structure, with clear goals that act like a red thread. These goals have to be visible to students and act like a guide that helps students to not feel lost in the learning process, offering them an indicator of which direction to move in.

By showing the relationships between learning units we hope to further manifest guidance and additionally create an understanding of why certain topics are being learned. In this context, it is also important to clearly define the goal of a given learning unit and specifically describe what should be understood.

All of the things mentioned above, aid in simplifying the material and in keeping an overview of the learning process, setting goals and evaluating progress, which in turn creates motivation.

The requirements that we take from this are:

R3.1 The concept shall make the structure of the content transparent towards the student.

R3.2 The concept shall reveal intentions and learning goals behind a unit.

R3.3 The concept shall make the relation between the learning units transparent towards the student.

4.2.4 Prevent Cognitive Exhaustion

As we have a diverse target group that includes students that do not know a definition of what a NN is, we formulate one of the main points of this design principle in accordance to D15 of the AI literacy framework. That is to assume that a student has no skills in AI, and thus to design the material to be accessible to everyone in order to motivate and not frustrate new learners.

It is worth mentioning the "canonisation" idea of the AI-Atlas [SKGW21], which wants to identify central topics and at the same time reduce the space of topics that one explains in a didactic concept. In this way, one reduces complexity and makes sure that important and central topics are emphasised and thus understood well. As our aim is to provide material for beginners, we want to motivate them instead of frustrating them with too much (and too complex) information. The understanding of the content is not only dependent on the transparency of the structure of the learning units but also on the manner in which they are constructed.

As [SAK11] argues, the intrinsic load can not be reduced but managed by breaking down complex topics. Here, our study participants mentioned that they prefer small self-contained units that build on each other. As such our concept should structure the content into self-contained, digestible learning units, that each focus on a single topic and build on one another. This leads to the next point of this design goal: We will design learning units which unveil content gradually. This way, the complexity slowly increases by chaining together small learning units.Independently of the approach, the learning units should be structured in a way that allows students to build on their existing knowledge and gradually increase the complexity of the content. In the literature, [LM20] it was noted: "To prevent cognitive overload, consider giving users the option to inspect and learn about different system components or explaining only a few components at once".

With respect to how the content should be structured on an abstract level, we note that the majority of students preferred a top-down approach, giving them a conceptual overview before zooming in on details.

As our study shows, a majority of students prefer the top-down approach, which allows them to see the big picture before learning the details. We believe, that the top-down approach facilitates the understanding of the relation between different topics, as they are easier arranged into the overall context, which in turn should lead to a deeper understanding of the overall topic.

In summarising all these requirements, we want to arrange the material top-down, but at the same time from simple to complex in modules that build on each other. To reduce the risk of overloading the students with information, it is important to give them time to process the information and to let them understand the topic before progressing to the next one.

All in all, we can list the requirements that can be deduced from our findings of the survey and the literature research as follows:

R4.1 Teach content in self-contained learning units.

R4.2 Structure the learning units top-down.

R4.3 Gradually unveil complexity.

R4.4 Give time to process the information.

R4.5 Lower barrier of entry by removing any hurdles for ,beginners

4.2.5 Interactive Design

For illustrative purposes, we summarise very briefly the results of [CdFP21] who identified problems that negatively influence learning behaviour. One of the problems the authors identified was if the material contains only text, which was shown to decrease motivation in students. While they stated, that long texts disturb the learning process, students however wished for visualisation and examples in context with NN to easier access complex and abstract information.

Overall, we hold, that optimal presentation not only facilitates the intake of information but can simultaneously also motivate learners if one minimises the extraneous cognitive load of learning materials.

Furthermore, our survey showed that students do not only want to observe material, but also interact with it to increase information intake and processing. It was also found in our survey, that external factors such as hobbies and friends often lead to a break in concentration. Hence, if we increase the immersion and engagement that students will feel with our concept, we decrease the effect of these disturbances.

In combination with the findings of our study, we believe that providing possibilities to directly interact and engage with the content. As presented in Section 2.1.3, those are exactly the effects gamification can positively influence. As such our concept should implement quizzes and challenges as we already mentioned before.

The points above result for us in the following list of requirements:

R5.1 Use challenges and quizzes.

R5.2 Motivate the topic.

R5.3 Avoid repetitive tasks and long texts.

R5.4 Provide Feedback.

D4: Prevent cognitive exhaustion	**D5: Interactive Design**
Provide students with the right complexity of information Break down a complex topic in small, digestible units.	Give students the means to directly interact with the educational material. Use engaging and enjoyable but still appropriate methods for this.
References: [LM20; SAK11; SKGW21]	**References:** [CdFP21]

5 A Proposal for a Game-Based Implementation of our Didactic Concept

In this chapter, we exploratory develop and discuss one possible implementation of our didactic concept in a self-study setting. To achieve our goal, we teach our competencies in the form of an educational game, where the previously identified design principles and competencies are to be implemented. We hope to exploit the positive influences of gamification on learning behaviour as discussed in Section 2.1.3. By implementing a holistic game we aim to create a low barrier of entry and a method that addresses a large target group.

In addition to our hope that this is a good approach for teaching NNs, the fact that standalone educational games without the guidance of additional material or lectures are not well-researched is another incentive to proceed with a purely game-based approach. The concept of our game is described in the remainder of this chapter. However, we do not provide an actual implementation, as this would be beyond the scope of this work.

5.1 General Structure and Storyline

We believe that having a meaningful story and character that students can build a relationship with by e.g. continuously improving the character, makes learning with the game immersive and engaging and improves motivation. At our university, there already exists a virtual hamster that is used to teach undergraduate students the fundamentals of programming. With our concept, we introduce a new figure into that "hamsterverse": The main character of our game is the "Robohamster". He lives in the distant future in a technologically advanced world, where hamsters substitute body parts with technical components to improve their skills and unused potential. As such, the Robohamster is basically a robot-hamster hybrid, who possesses among other things, technological body parts and an artificial brain the size of a planet, that makes him around 50000 times more intelligent than a smart person [Ada80]. Students can directly interact with the Robohamster: they control the hamster and interact through him with in-game elements and other characters in the game world in order to progress through the levels. At the same time, the Robohamster acts as a guide for them by e.g explaining tasks in levels to the students

The setting at the beginning of this game is that of an advanced world, where body parts of the inhabitants (hamsters among others) are substituted with technological parts, which sets the stage for thinking about NNs and motivates the "high-tech approach".

The background story behind the start of the game is the following: After a technical failure, the Robohamster's brain component is severely damaged and he finds himself unconscious, locked inside his own brain. The idea is that in order to regain consciousness, he needs to escape his brain, which he can do by repairing the brain's structure.

After the player has mastered this level, successfully freeing the hamster and regaining consciousness, the hamster finds himself lost in some wilderness. Given that he is no longer in the high-tech world that he originally grew up in, he has to learn how to survive and thrive in order to build a new life in the wilderness.

The entire game is formulated to be played in a standalone manner, without the need to read through an additional lecture, as the framework is intended to be used by students in a self-study setting. The game is thought to be independent of a lecture. The game is structured as described in the following: Levels are clustered into three overarching topics. These three topics each focus on a different aspect of NN and are graphically depicted as floating islands in our game (see Figure 5.1):

- **Awake**: Robohamster is unconscious and his consciousness is trapped inside his destroyed brain. In order to wake up, Robohamster must rebuild the damaged structures. As such this area mainly focuses on the structures of a NN.
- **Survive**: Once the hamster gained his consciousness again, he finds himself in an unfamiliar environment—nature. Far away from the technological city he is used to, he now needs to learn new skills, that help him survive in this unfamiliar environment. This area strongly focuses on concepts behind learning in a NN as well as data in a NN.
- **Rebuild**: The Robohamster wants to stay in the wilderness where he now looks for a hamster lady to rebuild his life. This area aims to integrate all the previously learned topics, with a strong focus on focus on applying the concepts on a toy project inside the hamster world, i.e. building and training an NN "from scratch"

In order to progress to a new area — to “unlock” a new area —, the player needs to first complete all levels in the processing area. The levels are independent minigames or puzzles that are connected by the game’s story.

Thus, a world is one large learning module, that contains smaller modules - the areas - that finally contain the smallest unit: the levels. By structuring the learning content, we aim to implicitly reveal the context of a topic in the field of NN and to provide a clear structure for the learning process.

5.2 Implementation of the Design Guidelines

In the following, we suggest how to implement the design principles defined above in the context of our game. For each principle, we look at the requirements as defined in Chapter 3 and suggest game mechanics or other types of implementation to fulfil the requirements of the design guideline.

Many story-based video games often include a video sequence, also known as game intro, in the beginning, that introduces the player to the world.We envision such an introduction for our game to on the one hand motivate the topic of AI and NN. On the other hand, it serves to motivate the topic of AI and NN by telling the story of how the hamster world became a tech world and why hamsters decided to modify parts of their body with technology. It also touches upon the context of neural networks in the field of AI by stating that the brain of the hamster mimics a biological brain. This could further be aided by linking elements of the game world with AI or ML topics. E.g. the introductory video could explain why hamsters decided to enhance body parts with intelligent technology. It could further describe what problems with the different types of body parts are known in the hamster society.

Req.	Goal	Implementation
R1.1	Visualisation of the learning progress	Upgrading the hamster Visualise locked and unlocked levels differently
R1.2	Reward for achievements	Collectibles to unlock content Collectibles to upgrade hamster Badges for ...
R1.3	Achievable tasks	Small, self-contained levels
R1.4	Provide help	Help button in levels Links to additional content in levels and library

Table 5.1: Requirements on “Make Success Reachable” and their proposed implementation.

Figure 5.1: The Overview Screen. Here the player can navigate between levels and sees his overall game progress. From this screen, the player can also enter the “Mountain of Knowledge” by clicking on the glowing mountain.

The main game consists of four main screens — the level overview screen, the library screen, a screen for each level and the hamster skill screen.

Figure 5.1 shows the level overview screen. This screen depicts the hamster’s road map towards the end of the game. It gives an overview of the number of levels, to which section – awake, orientate, survive — they belong and how far the player is progressed in the game.

Req.	Goal	Implementation
R2.1	Adjustable learning experience	Different skill branches Free choice of challenges Self-paced learning in Library Repeatable levels and challenges
R2.2	Varying presentation of content.	Links to external resources Library with different resources

Table 5.2: Requirements on “People are different” and their proposed implementation.

The three sections are represented as flowing island and cluster levels into overarching topics. In “Awake”Awake content covers mainly structural and very fundamental parts of a NN. The levels of “Survive” cover content about data and learning and the island “Build” integrates the two aforementioned topics To avoid long texts that disrupt the student’s learning progress as well as the gameplay, we intend to give instructions, explain tasks, or explain content either in form of dialogues with the game’s characters or by integrating short text-based information in game elements as exemplarily shown in Figure 5.7.

The game’s goal is to complete all levels and build a new life for the hamster in the wilderness. Students can only advance to the next level if they complete the previous levels first. Once a level is unlocked, students can repeat it if wanted. Progressing in levels is needed for the story to continue. In order to unlock new areas, i.e. get from one floating island to the next one, the students need to achieve two things:

- The student needs enough coins. Those can be collected in challenges and exercises in order to motivate further engagement with the topic at hand.
- He needs to solve a quiz covering all the previously learned topics to ensure that he properly understood the previous content. Again the quiz should challenge the student to further studies using game elements such as books or challenges

To address R1.2 each level starts with a short introductory screen that includes a title, and a short description of the level’s goal that directly tells the player what shall be educationally achieved in this level. Levels should be designed in a way, that the information they address directly builds on each other. To address R4.4 jumps in complexity between two levels that directly follow each other should be avoided. Additionally, topically related levels should be visually designed in the same way, making the student aware of this relation..

We implemented the library screen as shown in Figure 5.2 in form of the “Mountain of Knowledge” into our game to provide a clear and definite way of presenting the context and connections between the content taught at different levels to the player.

With the library, we aim to implement the requirements for the design principle “Structure and Transparency”. To that end, the “Mountain of Knowledge” is a screen dedicated to collecting and presenting learned content in a structured manner by utilising the concept of a library. Bookshelves contain books for an area of the game. Each book holds written information for one related level; it acts like a lecture script for one level. To address R4.3, a book can only be accessed if the associated level is completed. In addition to the level link, books also contain the goal statement

Figure 5.2: The library insight the "Mountain of Knowledge". On this screen, the player can collect and access theoretical information in form of books. The player can also create an "cheat sheet" by adding notes to the notebook.

Req.	Goal	Implementation
R3.1	Reveal structure of content	Bookshelves and Books in Library Topical islands with associated levels
R3.2	Reveal indented learning goals of a unit.	Books include learning goal Introductory Level Screen
R3.3	Unveil relations between topics	"Table of content" in Library Notebook in Library

Table 5.3: Requirements on "Structure and Transparency" and their proposed implementation.

of the belonging level i.e. stating what learning goal should be achieved. It also contains links to external existing resources link e.g. YouTube videos. Furthermore, books are colour coded to differentiate between their content e.g. books that cover an application-focused topic are yellow. To easily access content and with respect to R3.3 further reveal the relation between topics, a book can be opened by selecting it via a table of content associated with the bookshelf. In the library, the student can learn, repeat and deepen information in a self-paced manner thus implementing the requirements of "People are different".

Req.	Goal	Implementation
R4.1	Self-contained learning units	Small independent levels
R4.2	Top-down approach	General structure of the game
R4.3	Unveil Complexity gradually	Level that content-wise build on each other Need to unlock levels
R4.4	Enough time	No time limit in the game.

Table 5.4: Requirements on "Prevent Cognitive Exhaustion" and their proposed implementation.

Req.	Goal	Implementation
R5.1	Use interactive elements	Gamification of the concept
R5.2	Motivate the topic	Introductory video
R5.3	Avoid repetitive tasks and long texts	Use dialogues to provide information Use different game mechanics
R5.4	Provide feedback	Help button in levels

Table 5.5: Requirements on "Interactive Design" and their proposed implementation

The library also includes a desk space where the student has access to a notebook. The notebook is thought provides an overview of the whole topic of NN in form of e.g. a mind map. The student can extend this mind map with his own notes or links to either in-game resources or resources outside the game. The notebook is intended to be a "cheat sheet" that the student can use outside of the game. By doing so, we implement R2.2 and R3.3 with the notebook.

A so-called skill tree is an essential game mechanic in a large number of popular computer games used to enable a player to customise the game character they play. The idea behind such a tree is to provide a graph of possible character skills or traits that can be unlocked successively. This is a convenient way of defining hierarchical skills and also allowing the player to flexibly choose what they want their character to be capable of. An exemplary skill tree could for instance consist of two different branches, where a character could either develop magic skills or lock-picking skills, which successively can be upgraded independently of each other. An often-used mechanic is to require the player to collect different types of currencies which in turn can be used to unlock skills on the skill tree.

In this work, we attempt to utilise such a skill tree to aid in teaching NN concepts. It is our reasoning that this mechanic is very well suited to our stated teaching goals. For instance, one can imagine different branches in the skill tree, allowing the student to either choose a maths-heavy path or an application-heavy path etc. Unlocking steps in a skill tree can be achieved by collecting currency that is awarded in challenges and quizzes covering the desired skill. One can then increase the in-game characters' propensity to engage in certain challenges and quizzes which focus more on the chosen sub-tree. Instead of allowing the character to perform in-game skills, however, we propose that improvements to the hamster's outfit seem more suitable. In our stated example, this could entail the character retrieving a lab-coat once they have progressed some steps in the maths skill

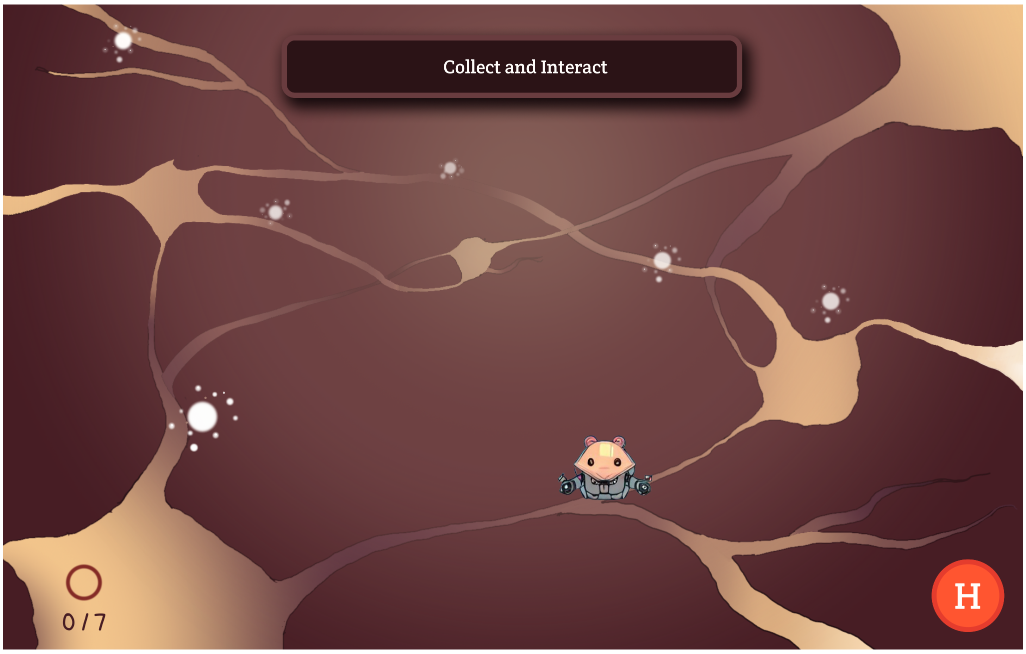

Figure 5.3: Skill Screen

tree. It is our hope that this allows students to better choose their preferred learning goals and let them modify the game mechanics to their preferred mode of learning, covering the requirements of the competency “People are Different” and furthermore motivate them by rewarding them with “badges”, “skins” etc. Instead of overall progress in the game, the hamster’s skill tree shows individual learning progress adding another facet to R1.2.

5.3 Introducing Game Concepts to Foster Competencies

Here, we list conceptual ideas for games and puzzles which try to address the competencies that we defined above. Where possible, we want to formulate these games and puzzles as general concepts in order to make our ideas reusable.

In our game concept, one game corresponds to one level that a player has to master. All of those levels, which we present here, are not fully developed and we do not provide details of some level descriptions, i.e. in our results that we present here, we do not aim to cover the entire topic of NNs. Rather, we want to present games as ideas for a general concept that might be used in a modified way for different topics of NNs. Furthermore, we would like to note that one game might address more than one competency, which is why in addition to introducing our game idea, we also list the corresponding competencies.

Game Idea: Collect and Interact This game is mainly targeting “C1:NN Strength and Weaknesses”. The core game mechanic of this game is that of platform games. Underlying this type of game is the idea of the player having to move on platforms while avoiding obstacles and collecting

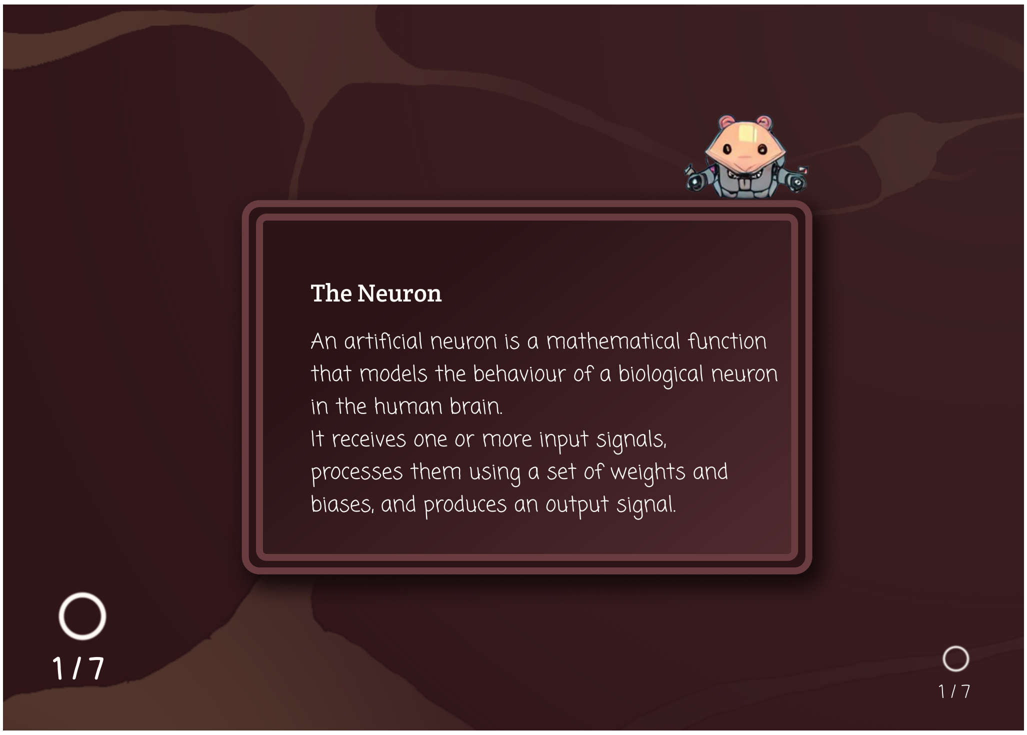

Figure 5.4: Information collected in the game concept “Collect and Interact”. This card will later be used to drag and drop it onto a visualisation of the NN in order to “repair” the NN.

items to reach some type of goal. One famous example is the game Super Mario by Nintendo, where the character Mario can move around on two-dimensional platforms, collecting coins and other special items in order to achieve the ultimate goal of freeing a princess.

In our game concept as shown in Figure 5.3, the hamster needs to manoeuvre through his brain to collect information about the structural components i.e. the fundamental terms of NN at checkpoints. In this way, the player exploratory uncovers new terms (Figure 5.4). The main challenge of this game is the control of the hamster and not so much the interaction with the content of the collected terms. To to more directly interact with the terms, one could imagine a game which focuses more on the content of the fundamental terms by requiring the player to associate terms with a visualisation of a NN, e.g. with a drag and drop approach. Alternatively, we imagine a game to learn about fundamental terms as point and click game to promote interaction with NN structures and think about relations between components. Point-and-click games are a sub-genre of adventure video games, where the player interacts with the story and progresses by exploring and solving puzzles. An illustrative example would be that the player has a lamp and needs to find a matching item to light the lamp in order to access the next room, which is currently plunged into darkness.

Applying this scenario to NN such a possible chain of interactions might be: the player needs to find a weight to connect two neurons. However, the definition of terms has to be provided when found and the player needs the possibility to re-read the definition. In such a game concept, the student might have many items in his inventory, but it is not unveiled which item has to interact with another in order to achieve something, which in turn enables learning through exploring.

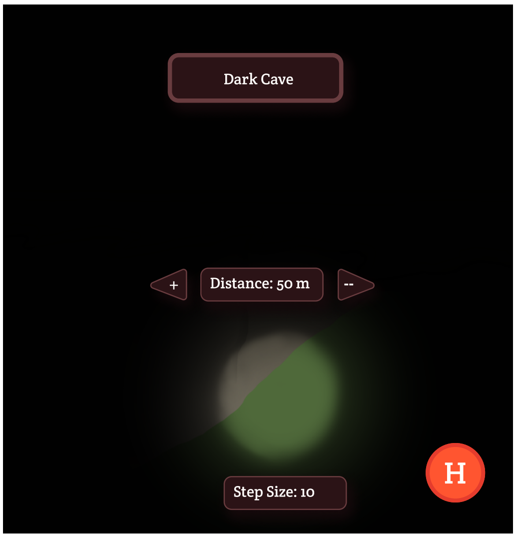

Figure 5.5: Game Concept of the game “Dark Cave”. The player needs to safely cross the canyon by finding the point, where the distance to the other side is minimal.

Game Idea: Dark Cave This game is inspired by a course on the KI Campus, where students try with the help of probes to find a treasure that lies on the lowest part of the sea. For a screenshot of the treasure-hunting game, see Appendix A.2.3. In our game concept, the Robohamster is in a dark cave and he needs to cross a steep canyon to get to the outside in order to find food. However, since it is so dark, he only has very limited sight. As seen in Figure 5.5, the Robohamster can only see the edge directly in front of him. He also knows what happens directly to the edge’s left and right—is the canyon getting smaller or not to each side? He also has an indication of how wide the chasm is at that particular point that he is located on. Based on this information, the player can decide in which direction the hamster should move, and how big of a step they want to take in the next turn. If the player thinks they found the narrowest part of the valley, they can attempt to cross it. The success of this attempt provides immediate feedback to a player, telling them if they have succeeded in finding the global minimum—the only part that the hamster can cross.

The basic principles and competencies that this game is teaching can be described as follows: The boundary of the valley represents the (one-dimensional) loss function of a neural network, hence the task of finding the narrowest part of the valley corresponds to finding the global minimum of this function, i.e. the abstract goal of NN training. By providing only the current width and direction of increase/decrease of the distance to the left and right, we symbolise the knowledge of the current value of the loss function, as well as the knowledge of the derivative. As this is exactly the information that a gradient descent optimiser has access to and utilises, this game teaches the basics of gradient descent optimisation. As such this game concept is addresses the competency “C3: NN Learning”

Game Idea: Save the Frog Generally, the idea of this game is to utilise the game mechanic of bringing algorithm snippets into the right order. After having successfully brought Robohamster, the hamster to the other side of the valley in the previous game, in this game the goal is to aid Robohamster’s friend, Franz the Frog, in crossing this valley, too. The idea is for the student to have to put into words the procedure that they have explored in the previous game. To this end, they

Figure 5.6: Game concept of the game "Save the Frog". The player needs to build a bridge for the frog. To do so, he needs to bring an algorithm in the correct order by dragging and dropping text blocks of the algorithm in the correct order onto the bridge. As the cave collapses, the player is limited in time.

are to put snippets of a pseudo-algorithm describing the optimisation procedure in the correct order. Essentially, they are writing a gradient descent algorithm this way, formalising the intuitions gained in the previous step and simultaneously learning how the mechanism behind NN learning works in detail. Furthermore, they learn to use the concept of a mathematical derivative inside of this algorithmic description.

A new dimension of learning is introduced in this game concept by also imposing a time limit in which this level is to be completed. In this case, this is shown as the cave slowly collapsing, which hopefully adds to the excitement of this task and creates a sense of urgency.

Game Idea: Building Bridges With this game concept, we follow an idea similar to the game Brain Bug [1], where the player gets to experiment with the structural components of an NN, especially with the activation of neurons and the architecture of a NN. We attached screenshots of this game inAppendix A.2 to give insights into the game's design In our approach, the hamster needs to connect and activate neurons by setting in going weight and thresholds in order to "activate" a bridge, that allows him to reach the next island close to one another—a convenient way of visualising NN outputs. In Figure 5.8, we present a sketch of how one could imagine the concept of such a game. Instead of numbers, we can imagine using different representations of the NN inputs, e.g. different representations of data such as pictures. Similarly, one can exchange numerical outputs too for instance labels.

[1] http://biologic.com.au/bugbrain/

Figure 5.7: Example of how a player receives information or instructions in our game.

Of course, the displayed NN is fairly simple in its structure and thus, the game can easily be extended to more complex NNs. Furthermore, one can also implement a flexible approach such as the one displayed in the ladybug game, where neurons and connections can be added to the network at will by a drag-and-drop mechanism, allowing players to choose what architecture works best. With this game concept, we aim to foster the competency *NN Structure*.

In contrast to Bug Brain, we want to refrain from using long, text-based explanations and rather interactively display instructions for the game in a dialogue-style menu with the Robohamster hamster character. Instead of having a monolithic text that explains the basics of a given level in the game, we imagine that the hamster gradually explains what the player needs to do. By going from implicit to explicit explanations, we want to gradually build a student's knowledge in a more didactic manner.

Game Ides: Good or Bad This game is inspired by the classification game of ArtBot [VZS+21]. Again, we provided screenshots of the game in Appendix A.2.1. The idea of this game is to let Franz the Frog explain what items are healthy food and what items are dangerous and should not be eaten. This he does by providing images with labels.

Then, in the first step, the player has to provide labels for unlabelled images after having seen a few examples of healthy or dangerous items. In the next step, the hamster should be able to label images by himself. To this end, one can already use a pre-trained NN which can successfully determine the class differences between images. In this game, it is important to provide a visualisation of how the hamster comes to a particular conclusion. This is also implemented in the ArtBot game in the form of a decision tree, however, we instead want to opt to visualise the inner workings of the

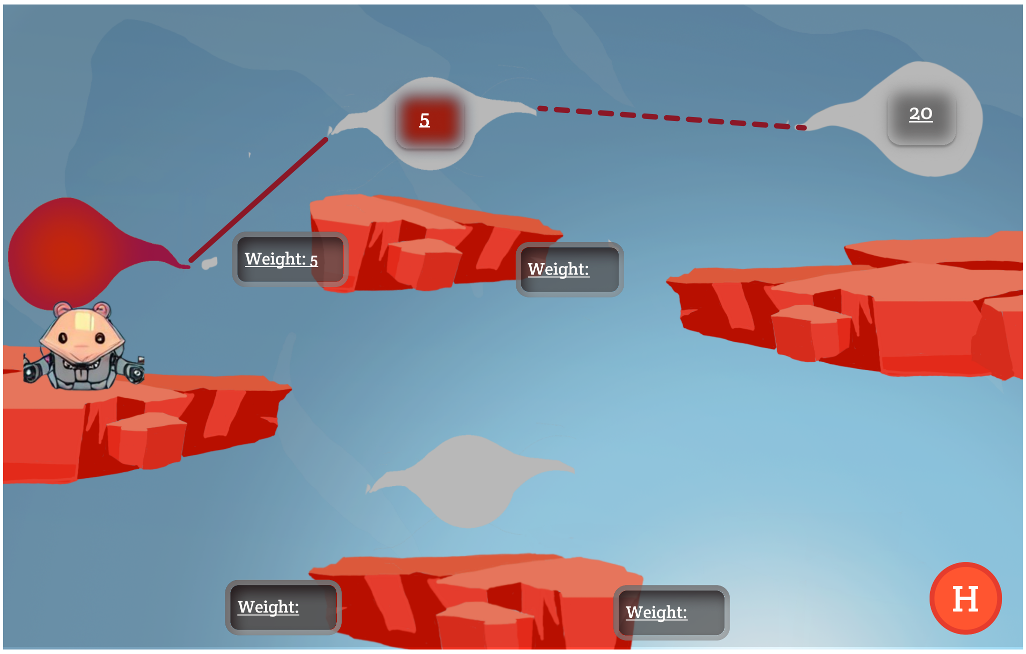

Figure 5.8: Game concept of the game “Building Bridges”. The player solves puzzles by adjusting e.g. weights and threshold in a NN in order to activate a way to the next rock.

underlying trained NN. One can achieve this by displaying the activation of each NN by colouring each connection according to its activation. We also want to display the output in a way that shows that the NN is not always confident in its prediction.

This concept aims to foster the competency “Role of Data”, by teaching the student how a NN interprets data and how labelled examples might be used to infer the labels of previously unseen data.

In yet another part of this game, we introduce a problem caused by algorithmic bias. The Robohamster tries to make new friends, however, everyone is scared of him since they only possess data to classify the hamster as a foe, not a friend. Some of these NNs outputs are to be in "word form", describing why they have categorised him in the foe category, while others provide image data that was used to learn about the hamster, which will help the player to determine the reason behind the hamster being recognised as dangerous. The goal of the player, then, is to identify the reason for this classification. To that end, the player needs to provide newly labelled data to the NPCs that clearly distinguish him from foes. For a more complex level, one could think about adapting a NN in order for the other NPCs to categorise the hamster into the "friend"category.

As this game mechanism strongly emphasises the understanding of data, we aim to foster the competency *The Role of Data*

Toy Project: The Perfect Hamster Lady This part of the game consists of multiple levels. The idea is to present the player with a toy project inside the hamster world, at the end of the game, that integrates the learned content. One part of this project which we labelled with “NN or not NN?” addresses *C1: NN Strength and Weaknesses*. For this game, the Robohamster is presented with different scenarios and problems and has to decide when and for what a NN can be used. One example of this type of task is: Counting how much food is left for the winter. Furthermore, in order to make this approach more challenging one could introduce a time limit, increasing the sense of urgency in the player.

In the same project, one can learn to actually create a NN with e.g. drag and drop mechanics and use those to solve puzzles, somewhat analogous to the Bug Brain. Further games that are to be included in this section are games, where one selects training data, and finally trains the NN on said data in order to apply the trained NN and find hamster ladies for Robohamster that correspond to his ideal criterion. The goal and idea behind the entire toy project are for Robohamster to find his perfect hamster lady to start a new life in the wilderness with, which would be the conclusion of the entire game.

6 Evaluation

In the chapters above we developed and didactic concept and an implementation proposal by exploratively introducing game concepts and elements to implement the didactic concept in form of an educational game. We now strive to evaluate whether the design principles motivate students and whether the concept covers all important competencies to teach PhD students the fundamentals of NN. Furthermore, we aim to get feedback about the implementation of the didactic concept as an educational game. Particularly, we want to investigate whether such an approach would appeal to PhD students in terms of motivation and learning experience.

To that end, we conducted interviews that were targeted towards obtaining feedback and counter check proposed didactic concept. We target two kinds of interviewees, that differ according to their experience with NN.

Interviewees that already work with NN in their research were classified as “experts” in the field of NN. We explicitly targeted experts to participate in our interview, since they can provide well-founded feedback regarding the competencies of our didactic concept. In the other group, we interviewed representatives of our target group, i.e. those that we labelled as “beginners” for our interview. This group focuses on the evaluation of the design principles and whether they motivate the learner if they can imagine learning with a game-based approach. We interviewed three people individually, two of them were “experts” and one of them a “beginner”, for approximately 30 minutes each. The general structure of the interview is as shown in Table 6.1.

We conducted semi-structured interviews in order to allow individual feedback, discussion and further thoughts regarding our concept and its game-based implementation, but still answer our core questions. In the remainder of this chapter, we present the interview results and discuss our findings.

6.1 Results

Because we are interested in how well the proposed concept covers the needed content and competencies for beginners, we first look at the results obtained by interviewing those identified as experts regarding NN. With this we want to evaluate whether the concept covers the relevant aspects of NNs. In the second part of this section, we aim to verify whether the design of the concept motivates students to learn. This is the reason why we present in the second part of this section the findings obtained by beginners, were we focused on design principles in the interview questions. Next, we focus on evaluating the games that we proposed. Lastly, we present our results from the open part.

One of the points of interest in order to later judge the interviewees’ statements, was the evaluations of the player types that our interviewees gave. Having information about what elements the interviewees normally like in games later helps us to classify their statements regarding game

<table>
<tr><th colspan="2">Interviewee classification</th></tr>
<tr><td>Beginners</td><td>Experts</td></tr>
<tr><th colspan="2">Questions about the interviewees</th></tr>
<tr><td colspan="2">What is your field of study?
What is your experience with NN?
How are NN related to your work?</td></tr>
<tr><th colspan="2">Presentation of didactic concept</th></tr>
<tr><td>Focus on design principles
Time to understand the design principles</td><td>Focus on competencies
Time to understand the competencies</td></tr>
<tr><th colspan="2">Questions about the different components of the didactic concept</th></tr>
<tr><td>Do you miss a design element?
Does their implementation motivates you?</td><td>Are the competencies complete?
Do you miss a competency?
Are the competencies appropriate for PhD students?</td></tr>
<tr><th colspan="2">Presentation of the game concepts and feedback regarding the game concepts</th></tr>
<tr><td colspan="2">Do you feel the concepts help you in understanding concepts of NN?
Would you like to learn with such a game?
Is this game-based learning appropriate for PhD students (compared to existing concepts)?</td></tr>
<tr><th colspan="2">Open Discussion</th></tr>
</table>

Table 6.1: An overview of the structure of the conducted interviews, including core questions.

mechanics. Interestingly, none of the interviewees could decide on one player type. All, however, indicated that even though they could somehow identify with all of the dimensions, for learning games they see themselves as a mix of Achiever and Killer. Additionally, they deemed the social component as important, since this presents you with "real people" who you can challenge. However, we could not definitely tell whether competing with real-world friends has a greater positive influence on motivation than competing with strangers since the answer differs from interviewee to interviewee. Nevertheless, all interviewees highlighted the importance of competition with existing people as a motivational factor for learning games.

With regards to feedback on the concept, we note that the interviewed experts considered the existing competencies and skills presented in the didactic as a good foundation. However, they had some additional remarks and mentioned extensions that they could envision in our concept. In the following we go over their remarks by looking at each competency separately.

6.1.1 Interview Results on the Proposed Competencies

For the competency **Strength and Weaknesses** the experts highlighted the importance of knowing the conceptual place that NN hold in the field of NN and AI. One interviewee mentioned that having an overview of ML and AI methods other than NN is very important, before zooming in on NN. Doing so once creates an understanding of the limits and intended purpose of NN as well as a holistic grasp of the context of NN in the field of ML. This should be underlined by knowing about different NN types e.g. dense NN and arguing what type of NN is suited for which application. Additionally, the concept should also introduce and differentiate between common problem types e.g. classification and regression.

Regarding the competency **NN Structure**, one of the experts observed, that going too much into detail might not be useful for a part of the beginners and the use cases they probably face. He stated, that obtaining a rough understanding of components and processes in NN is essential in order to work with them. This, for instance, includes knowledge of what a rectified linear unit function (ReLU) is and why is it so popular. We note, that trying to understand the optimal architecture of a NN however, is irrelevant for our target group. This is due to the fact, that learning about the subtleties of optimising the hyper-parameters is too complex for beginners. The expert mentioned that it is important to learn how existing NN for a given problem type behave and that it is useful to learn how to play with them. This includes learning how to obtain useful architectures via a trial-and-error approach. He mentioned that useful tools in this aspect might be TensorFlow or the TensorFlow playground.

While so far, we looked at the structure as a static component, we now consider the dynamic component, **NN Learning**: In parallel to what we already assessed, we make the following observation: It is well-known that learning currently is still a black box for researchers; currently, no one can definitively explain how a NN came to a certain result, but very simple and special edge cases. Nevertheless, both interviewed experts stated, that it is important to unravel this black box as much as possible. They argued, that it might not be directly helpful for students to understand this in detail. However, they said that an overview of the underlying mechanics is essential to not see ML as magic. One expert mentioned, that the level of depth for knowledge, i.e. deep formal knowledge, depends on the level of the "API" used to interact with a NN. He differentiated between an API for application and an API made for flexibility. The API he said is providing flexibility, is used for adaption in the structure and behaviour of NN and consequently requires more formal and detailed knowledge of NN than the API for the application. It follows, that for students the level of knowledge and abstraction depends on the problem that is to be solved.

In summary, it seems to be essential to get some kind of understanding of what the blackbox is doing while a NN learns, which includes the intuitive understanding of the underlying algorithm. Understanding NN at a level that would enable students to program/design completely novel algorithms by themselves seems not relevant in our case. Almost all PhD students that look into using NN for their research will be able to use either pre-defined models or can modify existing models and just call the optimise function provided by the NN framework that they use. For instance, in a framework like PyTorch—one of the most popular frameworks for NN—one can simply set an optimiser (such as stochastic gradient descent or Adam) and let the framework handle gradient descent. This knowledge then seems to be enough to "understand" their chosen type of NN. Of course, this is especially true given that a deep understanding of the learning process is at the current point in time not possible.

In the next part, we want to focus on the role that data and data selection play, according to our interviewees. With regard to the *The Role of Data*, our experts stated that it is very well known that nowadays not only a vast amount of content/ information exists, but that this vastness of data is also very useful for ML. It seems practical to partition this topic into more specific points, e.g. the influence of data on NN performance as well as on the correct filtering of data in practice. Furthermore, we briefly mention here that this is also a point that touches on the ethical aspect of NN, where any data which deals with living beings should be considered carefully and with careful consideration on the influence that a trained NN could have on them. However, as we found in the case of the research that most of the interviewed PhD students performed, this is not directly applicable, given that most of them did not focus on data or models that directly influence the lives of living beings.

One thing that all the interviewees agreed on is that this is one of the central aspects of using NN and that it should be very well described in educational material. Furthermore, they argued that it is important to be able to select the correct NN for a given set of data and that there is a big difference between just using "any kind of NN" for some data set and having found the optimal architecture for a given problem. With respect to what should be taught in particular, they mentioned that it is important to learn where to look and to be able to utilise existing resources. For instance, having been provided with data and a particular task such as classification, one can look at TensorFlow examples and start out with models that are provided there. The particular details of the used design choices were not judged as very important, e.g. the choice of the activation function is not too important, save for the knowledge that this is something that might be changed to better fit a given task. Furthermore, they emphasised the need of knowing the different known types of NN architectures.

Formalisation: It is very useful to learn the formal foundations of NNs, because—as was already discussed above–this enables students to be able to understand the literature and communicate their ideas to others. Additionally, one expert pointed out, that in his personal experience, it was very helpful to see, that he could directly translate mathematics into a part or function of NN.

However, they also emphasised that they would like the focus of such a concept to lie on the actual implementation of NNs in research, as this is what they felt most PhD students would be most interested in.

6.1.2 Interview Results on the Proposed Design Principles

Now we look at Feedback to design principles. The described implementation of the design principles as game mechanics was positively received. While the interviewee rated the existing design elements as helpful and motivating he pointed out the missing points:

Structure and Transparency: The interviewed beginner commented positively on the concept of making the structure a key design principle. He liked the implementation of gradually unveiling more content in the library bay unlocking new levels instead of having the whole content revealed at once since it would confuse a student too much. He emphasised the importance that levels are linked to theoretical resources and educational goals. This, he stated, gives the player student feedback about what he did and did not do and helps him sort out whether the thoughts he had while playing a game was correct. However, he stated, that more work needs to be done in terms of motivating the player to access the content collected in the library.

People are Different: With regard to the different learning behaviour of students, the interviewee remarked, that in his estimation two different types of learning speeds need to be acknowledged: On the one hand, there is learning speed, which describes how fast a learner picks up and processes new information. This was deemed adequately addressed in our design principles. On the other hand, the interviewee described the time that a person can invest in learning new information. This time differs from person to person and can be limited by external factors that the learner might not be able to influence like for example higher prioritised work even though it is implicitly in our concept formulated e.g. in the short units. Still, the interviewee felt, that this consideration needs to be explicitly addressed in the design principles. For all of the three interviewees content and learning experience that adapts to individual needs is one of the most important points, that would motivate them to use an educational game. While they found the already implemented game elements for customising the learning experience good, they stated that even more can be considered, i.e. by also adapting the learning content to the students' skill. This could be done e.g. by introducing quizzes where the difficulty adapts to the students' skill level. The discussion about customisable learning experiences leads directly to the findings for the next design concept.

Make Success Reachable: The interviewee highlighted the importance of individual components when defining what success means. He stated, that to a certain degree, the player should be able to decide what his learning goal is thus Skill tree again important.

He liked the idea of customising the character by collecting rewards from the game e.g. unlocking new skins for the hamster, which he felt helps with motivating and engaging students even more.

Complexity: Every person interviewed concurred that implementing a top-down methodology in our educational plan is the appropriate way to instruct newcomers in the basics of neural networks. Nevertheless, they emphasised that we need to place even greater emphasis on allowing students first to experiment with the application of NN before delving into the specifics. In this way, students will be able to see how NNs behave. Of interest is also a remark made by one of our interviewed experts: It might be possible that for students with a strong mathematical background, the preferred approach might be bottom-up. They said that they can envision these types of students preferring to first understand the concept of NNs, followed by applying them, which might also be an approach that the game offers.

The interviewed beginner noted, that we should pay attention to language in future work. He explained that based on his experiences, the language used by computer scientists is hard to understand by non-computer scientists. Thus, using a language that can easily be understood is important to reduce the barrier of entry to learning since students can easily access all the required information.

6.1.3 Interview on the Proposed Game Concepts

We also would like to note that one of the interviewees explicitly mentioned the need for a universal design, i.e. for the game to be consistently designed. This, he felt would help the learner student to navigate through the game, without getting confused about which part of the game corresponds to a challenge, which part should be learned etc. A uniform design might aid the student to reduce his extraneous load.

The interviewees deemed it important to strike a balance between the difficulty of understanding and having a repetitive game element Things that are easy to understand should not be repeated lots of times, otherwise, the game will quickly become boring and one can not see the value of the game.

With respect to our concept to motivate the topic of NN and also teach some concepts of AI in an introductory video, one of the interviewees stated, that there might be students that prefer to skip videos in games. Thus he suggested thinking about an alternative for this kind of people. He generally remarked, that it might be useful to separate between content and story in a way, that makes the story optional, i.e to have the option to play the storyline “on top”. This might help motivate students that have time problems since they can solely focus on learning progress and allow them to engage with the story only if they find the time for it.

Some of the proposed game concepts were very well perceived while others were not specific enough in order for the interviewees to really imagine them. This also made it hard for them to judge how well the listed competencies can be gained. The interviewees reported that concrete prototypes are necessary to provide more extensive than high-level feedback on the efficiency of the games. One game where they found the above mentioned in particular to be true, was the *Perfect Hamster Lady* game, where the participants remarked, that it lacks details in order to provide elaborate feedback. However, the interviewees liked the general idea of having such a component in the game, that puts together all the learned topics and lets the student apply them to a problem.

The game concept *Collect and Interact* faced the same issue of not being concrete enough. Additionally, the interviewees remarked, that they struggle with understanding how the game mechanics support learning since the heavy focus is on control instead of efficiently interacting with new information. Furthermore, controlling the hamster does not relate to a concept of a NN, so they could not see the connection between controlling the hamster and a learning effect. One mentioned, that he might fail to imagine learning like this simply because he does not know it. It could be hard, but it could easily be the difference and a fun way to learn the vocabulary of NN and might be worth further investigation. One of the interviewees proposed to introduce another screen dedicated to collecting and learning terms that are needed to unlock new levels that might improve the efficiency of learning.

Regarding the *Building Bridges*, i.e. the neuron weight games, the interviewees remarked that they would emphasise the experimental aspect more and that to them, this game seemed a little bit too straightforward. However, they found that the game achieves its goal of letting the student recognise the relation between the components that comprise a NN. In order to keep this positive aspect and make it a bit more “experimental”, it was remarked, one could gradually increase the complexity of the game and that one can introduce more features like sliders because these give intstant feedback to the player.

In contrast, all the interviewees commented positively on the *Dark Cave*, where students intuitively applied the concept of gradient descent function game. They also liked the subsequent following *Algorithm Game*. Both concepts were judged as good ideas to intuitively grasp formal concepts like gradient descent and cost functions. They also particularly liked that in the *Algotrithm Game* the previous actions are presented and thus recapitulated in a short text form. This, they found, gives the student immediate feedback about the thought process behind the algorithm. One of the interviewees stated, that the transition between those two games helps a student to connect the ideas in one’s mind. He explicitly commented on the fact that it is very useful to make a situation more complex while keeping the underlying concept the same facilitating the understanding of complex topics, which is true for the games where one guides the hamster over a valley and afterwards formalises this procedure in a prototypical algorithm.

The games that focused on data labelling were judged to be a good idea. The interviewees commented that this helps with visualising the probability character of training. Furthermore, they found that it provides a good way to experience learning and what might go wrong during training. The idea to label enemies in the wilderness in order to create such a data set, they found, demonstrates the treatment of data and the importance of data sets well.

Overall, the ideas were well perceived, especially the idea of having a library for learned information, that present the information in a structured and well-connected manner, which was judged equally well by both experts and beginners. They especially emphasised that the levels should explicitly link to this library in order to provide another feedback mechanism of which topic is important in a given level.

The interviewees said that they really like the very idea of the game concept we showed them. However, they commented that as PhD students they fear that one of the main problems is the limited time that students have. This, in their estimation, has to be reflected in a teaching concept that condenses as much information in as little time as possible. One of the experts explicitly said for instance, that he would put most of his focus on making the library as well-thought-out as possible, in order to provide a place with a very high information density.

Understandably, they felt that they can not yet judge if this density of information is achieved in our game or not, given that it has not been implemented yet and that they had only access to our concepts and mockups. It thus turns out that it is really hard to design a game for PhD students that are pressed for time and it might be the case that a game is better suited to teach—for instance—undergraduate students this way. However, we also note that these results are somewhat limited, as the interviewed students all came from science backgrounds and already had a technical background.

6.2 Discussion

In this work, we explored an approach to teach the fundamentals of NN to PhD students. To that end, we developed a didactic concept targeting the needs of our user group. The concept was based around competencies that are intended to foster on AI-Literacy as found in the literature, which was mapped and extended to our use-cause by us. We then investigated the implementation of the developed concept in form of an educational game. The proposed competencies and design principles were found to cover a good part of knowledge considered important for beginners and aided in motivating students.

When targeting such a broad target group as we aim to, we found that a game must be highly adaptive and customisable in order to create value for students individually. Alternatively, we found that it is sensible to formulate competencies and design principles broadly but to concretise the actual teaching experience one should engage with a student's individual needs. This is especially true in the case of PhD students as they have vastly different backgrounds and approaches that they have learned to use when learning new topics. Utilising a game-based approach requires careful consideration of the requirements. We found that this is mainly due to three reasons: One has to teach a complex topic in an approachable and easy way in games. The game has to be engaging for users, keeping in mind that users generally differ in their estimation of good games. Thirdly, it has to be useful to students which are already used to typical academic learning.

Another point that we would like to make is that a game-based approach is more suitable for first-semester students (or formulated more generally, for beginners that are not so used to "typical academic teaching"). Furthermore, we note that the students that we interviewed all came from a STEM background. With respect to the knowledge of the underlying technology of NN, these STEM students—on average—are more knowledgeable than students in other fields. Hence, we conclude that while we have validated our conceptual framework, i.e. the competencies and design principles that we present, and while our approach targets a broad target group, it might be necessary to rethink the size and composition of the group that we target.

Based on the findings of our conducted interviews, we now answer our research questions: **RQ1:***What does a didactic concept require to enable and motivate PhD students to learn the basics of neural networks?* Our didactic concept consists of a goal, design principles, competencies and a method and a setting of the implementation that are formulated with the needs of a specific target group in mind.

Based on our initial survey to define requirements in Chapter 3 and an exploratory literature review (see Section 2.3, we found that our concept should consist of competencies tailored towards PhD students to promote basic NN knowledge. In particular, the competencies that were found to be the most important were derived from three major questions of AI-Literacy and adapted from [LM20]to NN: What is a NN? What can a NN do? How does a NN work?

Most students want to know which type of NN can be useful for what particular task. They are interested to understand NN in an abstract, high-level type of way. How much this high-level knowledge is important depends greatly on the task at hand for a PhD student, where sometimes the type of NN used is already really clear. However, if a student has to develop an approach independently, then this high-level approach is really important. While the understanding of the detailed, mechanistic underpinnings of NN can be useful and important, we found that most students prefer to only learn as much as is needed to motivate a certain architecture choice for their project. Much more importantly, it was found, is it to be able to successfully train and deploy a model, which was found to be distinct things from one another.

With respect to approaches found in the literature, ethical aspects are highlighted as an important aspect of AI literacy and important for students to understand. It turns out, however, that in the case of PhD students, this topic is not so important, because it is fair to assume that they already possess critical thinking and a developed sense of ethics. Furthermore, their application of NNs usually is highly specific, such that the usual ethical considerations do not, often, apply. Hence, we recommend that ethics remain a part of a didactic approach, but that it only serves as a reminder to think about the topic and introduce controversial points, rather than be a central part of an approach targeting PhD students.

With respect to the level of formal knowledge that PhD students wanted to learn about NNs, we draw the following conclusions: Students view formal knowledge as important in terms of knowing what design choices they can make and in order to explain their motivation behind a particular NN choice that they settled on for a given research problem. However, students felt that the focus should lie on the high-level understanding, rather than a detailed mathematical understanding as they felt this is much more important in order to reach their goals in their PhD projects.

Summarily, all those points listed above, resulted in the following competencies for a NN teaching framework such as ours:

Apart from addressing the content that students deemed important and interesting, we also investigated what maximises the students' engagement and motivation. For this important topic we found 5 principles to be important: **??**

Of course the proper choice of methods that enhance motivation of students leads directly to the second research question, which we will focus on in the next part of this section.

RQ2:*Does the usage of our proposed game-based approach motivate PhD students compared with existing and used learning tools?* Here, we want to specifically emphasise our findings on whether the use of a game-based learning system seems to be the proper choice for teaching PhD students the basics of NN usage in the context of their research.

Generally, the idea of game-based for self-learning the topic of NN exciting approach to tackling the complexity of the topic.

Especially the implementation of design principles as elements of a game introduced in Section 5.2 were all deemed to have a positive influence on motivation and engagement. Especially important: fit learning experience to own needs. One proposal that we list here in order to further customise this is to provide adaptive levels, quizzes and challenges that react to the student's skill level. Equally important were game mechanisms that provide some sort of feedback on the correctness of their thoughts/understanding in the form of quizzes, and challenges but also learning goals and summaries of the learned information. To further supplement the principle complexity we emphasise the care that has to be taken to choose the right language and also to use consistent visualisation. Furthermore, we note that it is advantageous to visualise the learning progress in different dimensions, i.e. to display progress in the overall game and topic, as well as inside of the sub-categories. This could take the form of e.g. application-related content and progress for individual goals visualised as increasing the skill level of the Robohamster.

Here, we especially want to highlight the library that we implemented. It allows to concisely combine the games and the theoretical background of NNs as well as connect them with other resources and allows students/players to take their own time to learn those and look into them if they so intend to their desired depth.

For games, they mentioned that it is important to have the right density of information to make it attractive or PhD students. They mentioned that for them games that over-emphasise just playing in contrast to actually transmitting knowledge as wasteful.

In the case of the item collection game, Having a game where the player collects terms that are relevant to a given teaching goal was deemed a good idea, however, the interviewees again emphasised, that one always has to ensure that the relation those terms have to the overall context of the learning goal should be clearly communicated.

In the case of the game where the player has to choose the right weights of a model NN, it was mentioned that this is a case where trial and error really shines. While the survey participants had a hard time judging exactly how the game would feel when played, given that they were only provided with a mockup, they mentioned that it also could very well be a good introduction to the learning process of NNs.

The data, flashlight and algorithm were judged very positively as the underlying concepts appeared to be clearly stated. Furthermore, they praised that levels which build on one another were designed in a similar manner and thus allow the student to know what type of approach to use, despite an increase in complexity.

Having a toy project that integrates all the topics that students learned over the course of their game journey also was judged to be a very good idea. This way, a student really learns to apply the concepts that they learned only in theory so far. Generally, we found, that the game-based implementation of our approach is deemed to be motivating and exiting. However, concerns about the efficiency of the learning experience must be considered.

Although games can provide more motivation and fun, it is difficult to determine the efficiency of learning for PhD students, especially those with a scientific background, due to insufficient implementation. The novelty of using games as a learning tool is an added benefit for interviewees. However, when considering time constraints and the expected learning pace, it may be more effective to stick to well-known concepts such as MOOCs like Brilliant or Udemy. Proposed for undergraduate university students or for people that are not limited in time. Alternatively, we found in our interviews, that a viable solution for PhD students might be to centre a game-based approach more around the library, which additionally to motivating students also provides the opportunity to build a game concept with a stronger focus on learning.

Finally, we want to briefly discuss where our research fits in the theory of AI education. As we stated in the beginning, there is a gap between the usage of AI in society and the education of citizens. Many works address this gap by developing didactic frameworks and curricula aimed at fostering AI literacy. While these works often either span the entire K12 or target a specific K12 level, approaches to promote AI literacy for higher education and especially for graduate students are less researched. This leads to the following problem: university students, which represent a group for which the application of NN in their research might be especially advantageous, however, they often lack the knowledge of how to use NNs, especially if their field is not STEM-related. By doing a study and applying and adapting the existing AI Literacy framework, we created a didactic concept that explores how to tackle the aforementioned problem. By doing so, we hope to address this gap in knowledge and start work on creating didactic concepts specifically tailored towards university students, in particular PhD students.

However, since this is an explorative work, many points arise for future discussion which we will address in the next section of this chapter.

6.3 Future Work

As mentioned above, we found that our concept provides a solid foundation to further discuss an implementation of a learning tool for NN for PhD students. Due to the explorative character of our work, several important points to discuss for future works emerged around our research questions, which are not explicitly answered by our research questions.

One of these points is a direct addition to our proposed framework, in order to provide a better discussion foundation. It was highlighted by all of the interviewees, that the adjustment of the learning experience towards the user is necessary to maximise the effectiveness of a game-based learning approach. Acknowledging this need for a customisable and adaptive way of learning, we suggest introducing an individual design principle dedicated to addressing that (rather than having it implicitly formulated over / blended in with different design principles). To that end, we define the design principle “People are different” as a principle that aims to cover the needs of different groups in general. It is about making content accessible to a variety of people with different needs with respect to their learning behaviour. In contrast the new design principle “Adaptive and customisable learning experience” is all about the needs of an individual learner. It includes all features, that allow a student to individually design the learning process by setting individual goals as well an enhancing immersion by e.g. customising the hamster.

This leads directly to the next discussion point: As explained, having adaptive elements in our concept is deemed to be important. This, however, needs to open a discussion about the amount of customisation until In order to effectively utilise the positive influence of customisable game mechanics, it is necessary to investigate how many individual needs are covered with one concept. We think, that at one point one needs to think about further cluster arising individual needs and formulate new learning goals that specifically cater towards their requirements in order to avoid overloading one general concept with too many features, consequentially overloading the student. Future work should discuss, at what point it makes sense to break down the target group and develop different learning goals to address their needs.

Though to further specify the target group several points need to be discussed: One feature to differentiate between different target group targets the motivation of different students. The interviewees were in agreement that PhD students usually have a limited amount of time to learn the fundamentals and thus aim to learn new information as fast as possible and not necessarily as fun as possible. While we tend to agree with this sentiment, we can not confirm whether this motivation behind their choice of a learning approach is applicable to all students. This is due to only having 3 opinions that all were studying fields in STEM fields. It might be because PhD students generally aim to learn new information as fast as possible due to the time constraints of their work. However, it could also be that they do not know a different way of learning since seldom are exposed to different approaches to teaching. This is further emphasised by the statement of one of the interviewed experts. He mentioned, that he did struggle to imagine this way of learning, simply because he never learned that way And while he believes that many choose time over fun he could also imagine, that learning with a game could be great. However, to investigate this bias in our survey, which was due to the very natural science-focused interviewees and thus had already an entry point into this topic, we propose the following research question for future work to tackle: What reasoning influences the choice of self-study tools for PhD students? Which can specifically look at PhD students that do not have AI as their main topic of research.

Differentiating students by their academic background/fields of study might be one of the more obvious features that specify target groups. Nevertheless, even with this differentiation in place, it might be useful to further specify target groups. As we have seen in our initial study, it is possible to further classify beginners into different levels. When formulating our competencies we did not distinguish between those levels but rather tried to find common needs towards the content. It is imaginable, that a survey tailored to the different levels of beginners would result in competency and design principles that differ between the different levels. What might be appropriate for an absolute beginner might already be too much game for a beginner with mathematical background or someone who already had first experiences with NN but in terms of theoretical knowledge and/or application experiences is still considered a beginner. Since our work possesses an explorative character, we targeted a highly heterogeneous group with the only commonality being that they are PhD students interested in using NNs in their work. In future work, one might want to target the game towards a more specific target group in order to find more concrete requirements. It became clear that to have an implementation for our didactic concept, the target group needs to be further investigated to pinpoint their needs more precisely. This leads us to another question for future work: What kind of PhD students exactly are target group for game-based approach?

One discussion point concerns the amount of game versus the amount of information packaged in a didactic game. One needs to weigh the motivational effects of a game against the density of information conveyed in a learning unit. This entails thinking about whether every game mechanic needs a different learning effect or whether it is all right to partially focus more on games while putting information into the background. One example where this point became clear was the game where the player runs through the world and collects items. Here, the focus lies on controlling the hamster, the movement through the world is not connected with information about NN. The objects containing information on NN only incentivise the player to move through the world and play the game. In contrast, having a memory-like game, where the player e.g. needs to pair definitions with terms, focuses more strongly on the learning aspect than on the game aspect. The goal is to memorise and connect information, the game mechanics i.e. flipping cards are only supplementary to the learning process. This is exactly a point that arose in our interviews. Interviewees could not tell how much a highly gamified approach would appeal to learners. In accordance with our review and our study, we do not take the quantitative effectiveness of learning into account. Future works need to consider where this balance should lie. This leads us to the following question for future work: How much to include game mechanics in the game? As well as the question of: Is it ok to include game mechanics just to play if they do not directly yield theoretical input/output?

The answer to this question, we posit, can be found out by quantitative research on how much recall students have of the educational content in games with a strong focus on the game.

It is hard to find out on what level of abstraction one should communicate in order to efficiently teach PhD students. There are vast differences that depend on the way that NNs are used in a given field of research. An important point for future work is about the levels of abstraction that are needed for the application of a NN to problems. Our initial study showed, that our participants wanted to know most about how one may apply NNs. However, what does apply to mean in this context? We think, that what students understand as “applying a NN” strongly depends on their field of research and the problems they want to solve. Thus, future work can focus on the question of what constitutes as application of NNs for PhD students of different fields. If these questions are cleared through research, the complexity, levels of abstraction and level of detail can be factored into the teaching approach in order to increase the utility of our concept to students. In summary, we propose the following questions for future work: What level of detail is needed to efficiently apply NNs? What does “application” of a NN mean (for a given target group)?

6.4 Threats to Validity

Our work was to provide an exploratory approach mainly based on the findings of our survey group. We expect that provided a larger target group, the requirements that are obtained might differ from our initial results. In the case of the interviews that we held in order to evaluate our concept, we introduced a bias by having at our disposal only PhD students from STEM fields. We expect that this influences our results, especially with respect to their evaluation of mathematical concepts, in which they were well versed already.

Furthermore, the beginner that we interviewed was not a “full beginner” and already had some experience with NNs, which might also introduce a slight bias in what he estimated to be important for an introduction to the topic. Hence, in order to improve upon our work, future work might want to conduct another survey with more and more diverse interviewees.

7 Conclusion

In this work, we explored an approach to teaching the fundamentals of NNs to PhD students. To that end, we developed a didactic concept targeting the needs of our user group. The concept was on the one hand based on the findings of an initial study, targeting the needs and expectations of PhD students. On the other hand, the concept is formulated around competencies that are intended to foster AI Literacy as found in the literature, which we mapped and extended for our use case by integrating the findings of our survey. We then investigated the implementation of the developed concept in the form of an educational game.

The proposed competencies and design principles were found to cover a good part of knowledge considered important for beginners and which aims at motivating students. When targeting such a broad target group as we aim to, we found that a game must be highly adaptive and customisable in order to create value for students individually. Alternatively, we found that it is sensible to formulate competencies and design principles broadly but to concretise the actual teaching experience one should engage with a student's individual needs. This is especially true in the case of PhD students as they have vastly different backgrounds and approaches that they have learned to use when learning new topics.

Utilising a game-based approach requires careful consideration of the requirements. We found that this is mainly due to three reasons: One has to teach a complex topic in an approachable and easy way in games. Secondly, the game has to be engaging for users, keeping in mind that users generally differ in their estimation of good games. Thirdly, it has to be useful to students which are already used to typical academic learning. Another point that we would like to make is that a game-based approach is more suitable for first-semester students (or formulated more generally, for beginners that are not so used to "typical academic teaching"). Furthermore, we note that the students that we interviewed all came from a STEM background. With respect to the knowledge of the underlying technology of NN, these STEM students—on average—are more knowledgeable than students in other fields. Hence, we conclude that while we have validated our conceptual framework, i.e. the competencies and design principles that we present, and while our approach targets a broad target group, it might be necessary to rethink the size and composition of the group that we target

However, with our approach, it should be possible to implement a game, which PhD students find engaging and motivating and that includes the topics that they feel are most important for them to use NNs in their own research. It is our hope that software developers looking into fully developing such a game-based concept directly can apply our results, using them to generate a gamified course to teach PhD students the basics of NN usage. Furthermore, as we took great care in implementing exactly those topics that PhD students need in their research and by focusing just on the usage of NNs, PhD students might also benefit from the competencies developed in this work alone. Without a fully-fledged game available, these competencies still encompass those skills deemed to be most important one looks into the utilisation of NNs for research.

The obvious avenue for future work to improve upon our work is to actually implement the proposed learning game. While we provide concepts for some, full implementation of these was beyond the scope of this work. Furthermore, as was already mentioned above, it might be useful to carefully re-evaluate the target group in order to produce material which better caters to a specific group of PhD students, for instance only STEM students, because the gap in the knowledge might be too much for a single game to teach adequately. In keeping with this theme, having developed a full game, an additional survey is needed to validate the tentatively proposed design principles and to see if the retention of competencies is sufficient for PhD students to be able to use them by themselves.

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All links were last followed on March 13, 2023.

A Appendices

A.1 Initial Survey

A.1.1 Questionnaire

In the following we provide, verbatim, the survey as we showed it to the participants.

Survey: Requirements on a didactic concept for teaching the fundamentals of artificial neural networks.

Our goal is to create a didactic concept to teach the fundamentals of artificial neural networks (NN) to students of higher academic levels. This concept will be a base for the implementation of a learning tool targeting the aforementioned target group and goals.

Your answers will allow us to meet the knowledge level of potential users as well as gather their expectations on a design of such a teaching concept. Based on your answers, we will also determine what content to include into the concept and how to shape this content.

Your data will only be used in the context of this survey. For the evaluation of this survey, we will make your data anonymous.
If you have any questions feel free to contact us per mail: nn-survey@outlook.com

Thank you for your participation.

Estimated Time: 20 min

1. Content

In this section we aim to gain an understanding of the current knowledge level to determine the content and scope of the didactic concept. To that end, the following questions include questions about your knowledge in the field of NN.

Please answer these questions without any external help, since the correctness of your answers is insignificant in the scope of this survey.

Estimated Time: 10 min

1.1 How much experience do you have with artificial neural networks (NN)? *

	1	2	3	4	5	
Inexperienced						Expert

1.2 For what tasks/problems could NN potentially be used during your Masters/PhD? *

Please describe tasks/problems that could be solved/simplified with the usage of NN.

1.3 How will you use a NN for the task/problem mentioned above? *

Usage of existing NN including e.g. the analysis of the NNs output, the configuration of NN parameters and the selection of an activation function

Adjustment and usage of existing NN, i.e. changing parts of the NN's code before usage

Writing an own NN for your specific task/problem

1.4 What concept do you think most closely resembles the idea of NN? *

Decision Tree

Artificial replica of the brain

Mathematical Function

1.5 Imagine a system that will help you understand NN, what features do you expect? *

.

1.6 How would you define a NN? *

Please give a short definition of the term in 2-3-sentences.

1.9 Do you know tools for learning NN? *

Yes

No

1.7 Please try to give a short definition of the following terms: Back propagation, Artificial neuron, Activation function, Layers, Forward Mode

1.8 Where do you have difficulties when learning about NN? Please complete the following sentence by filling in the blanks.

While learning about NN the main challenge was/is for me ________ . I was/am struggling with understanding _______.

1.9 Do you know tools for learning NN?

YES

NO

1.10 Which existing tools for learning NN do you know? *

1.12 What do you like about the tools? Please give the tool names with your answer. *

Provide your answer in the form: name of the tool - things you like

1.13 How can the tools for learning NN can be improved? Please give the tool names with your answer. *

The following section is independent from your knowledge about NN. It contains general questions about your learning behaviour that help us design teaching material/learning units by understanding your preferences.

Estimated Time: 7 min

2.2 What do you consider most important for a good lecture? Please pick at most two of the below stated answers. *

- Comprehensible and cohesive structure of the content, clear relation between different topics of the subject.
- Intermediate quizzes to test knowledge and learning progress
- Clear and transparent communication of what is to be achieved
- Interaction during the lecture

2.3 What does a talk/lecture needs to provide such that you take away the most knowledge? *

- Plenty of graphic representations and coloured highlighting that supplement the content.
- The space for undisturbed listening, so that you can listen attentively.
- An interactive way of getting the content across, with questions and discussion.
- Practical examples that demonstrate the implementation and/or application of the content.

2.4 How do you stay motivated when learning about a new topic? *

2.5 What factors disturb your learning process? *

Please state, when you find it hard to start with learning a new topic and/or what negatively influences your motivation to learn.

2.6 What helps you when repeating a topic with the goal of deepening your understanding about the topic?

	1 (unhelpful)	2 (rather unhelpful)	3 (rather helpful)	4 (very helpful)
solving exercises/problems				
visual reprocessing the topic (e.g. crating mindmaps)				
watching and listening to videos				
creating and using flash cards				

2.7 Please complete the following sentence by choosing one or more of the answers: I am motivated to learn a new topic, when ... *

... my learning progress is clearly visible.
... I get a reward for learning activities (e.g. collecting points).
... the topic is highly relevant for my work.
... I can learn by doing and experimenting.
... the learning content is visualized.
... the learning content is highlighted by exciting examples.
... I can learn playfully (with games).
... I am interested in understanding the topic.

2.8 How do games that focus on teaching new content help you with learning a topic?

Describe, if and how gamification supports you with your learning process.

2.9 How could a game-like learning system that motivates you to learn look like? *

Please give concrete examples. If possible, state positive and/or negative examples from past experiences.

3. Further suggestions

This section contains a space for your additional thoughts and ideas for a didactic concept, if you have not had the possibility to do so in the questionnaire above.

3.1 Ideas/suggestions for content/design of the teaching concept.

4. Information about participants

Please fill in the following questions. Your data will only be used in the context of this study. Name and Mail will only be used for the purpose of contacting you.

Estimated Time: 3 min

4.1 What degree are you currently pursuing? *

Master
PhD

4.2 Please specify your gender *

Female
Male
Prefer not to say

4.3 What is the field of study you do your Masters degree/PhD in? *

e.g. Computer Science

4.4 What is your final thesis about?

4.5 Are you free for a follow-up interview around February 2023? *

Yes
No

4.6 Email *

only for the purpose of contact

A.2 Impressions of Educational Games

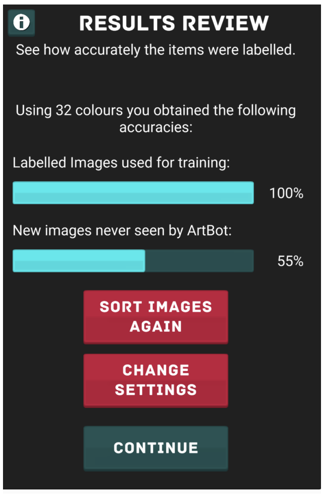
Links to the games:

ArtBot https://art-bot.net/

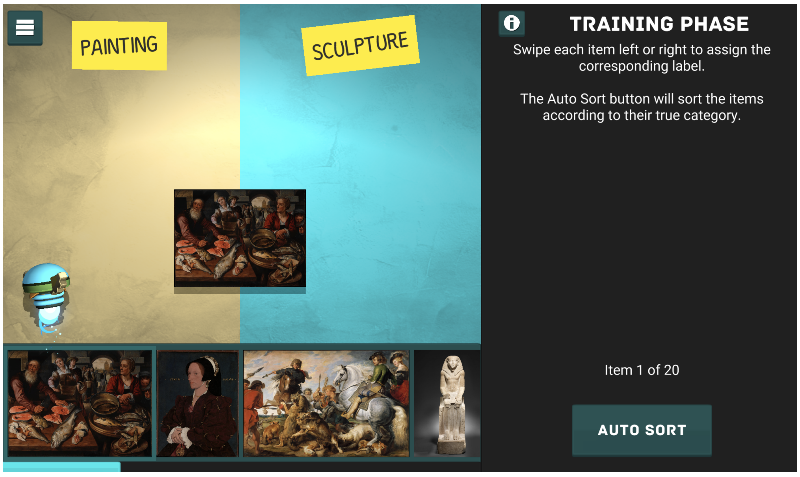
Bug Brain http://www.biologic.com.au/bugbrain/

KI Campus https://learn.ki-campus.org/courses/explorables-schule-imaginary2021/items/7H9nZI186JgjC8jOjxdbaT

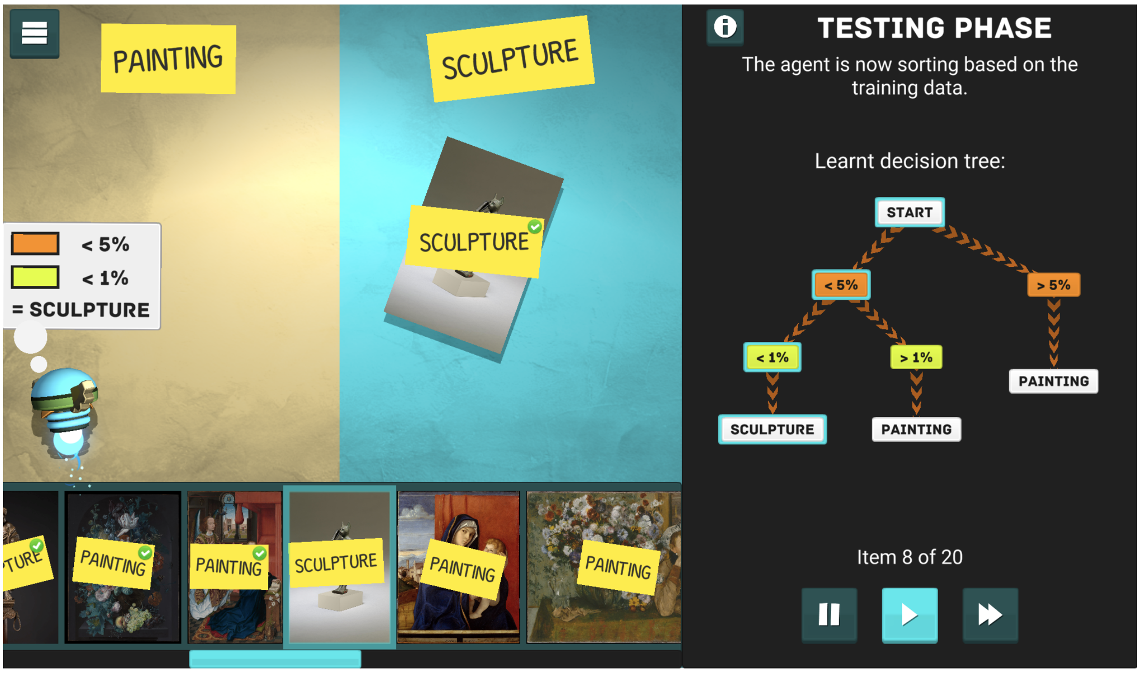
A.2.1 ArtBot



(a) Results after testing



(b) Traing Phase: Payer needs to drag and drop pictures and classify



(c) Artbot4: Testing Phase

Figure A.1: Impressions of the game "ArtBot"

A.2.2 BugBrain

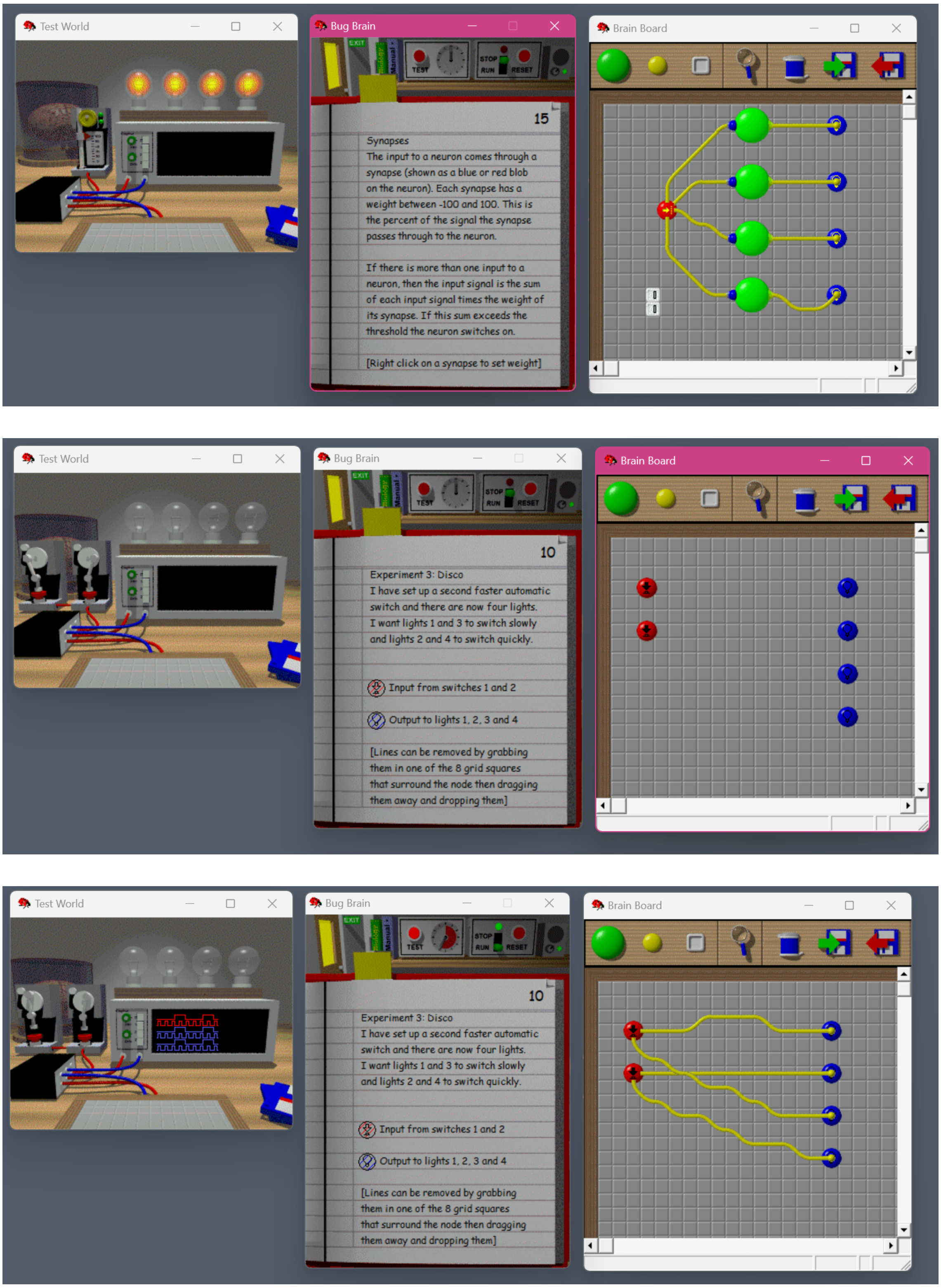


Figure A.2: Impression of the game “BugBrain”

A.2.3 KI Campus: Treasure Hunting Game

A.2.4 GradientDescent

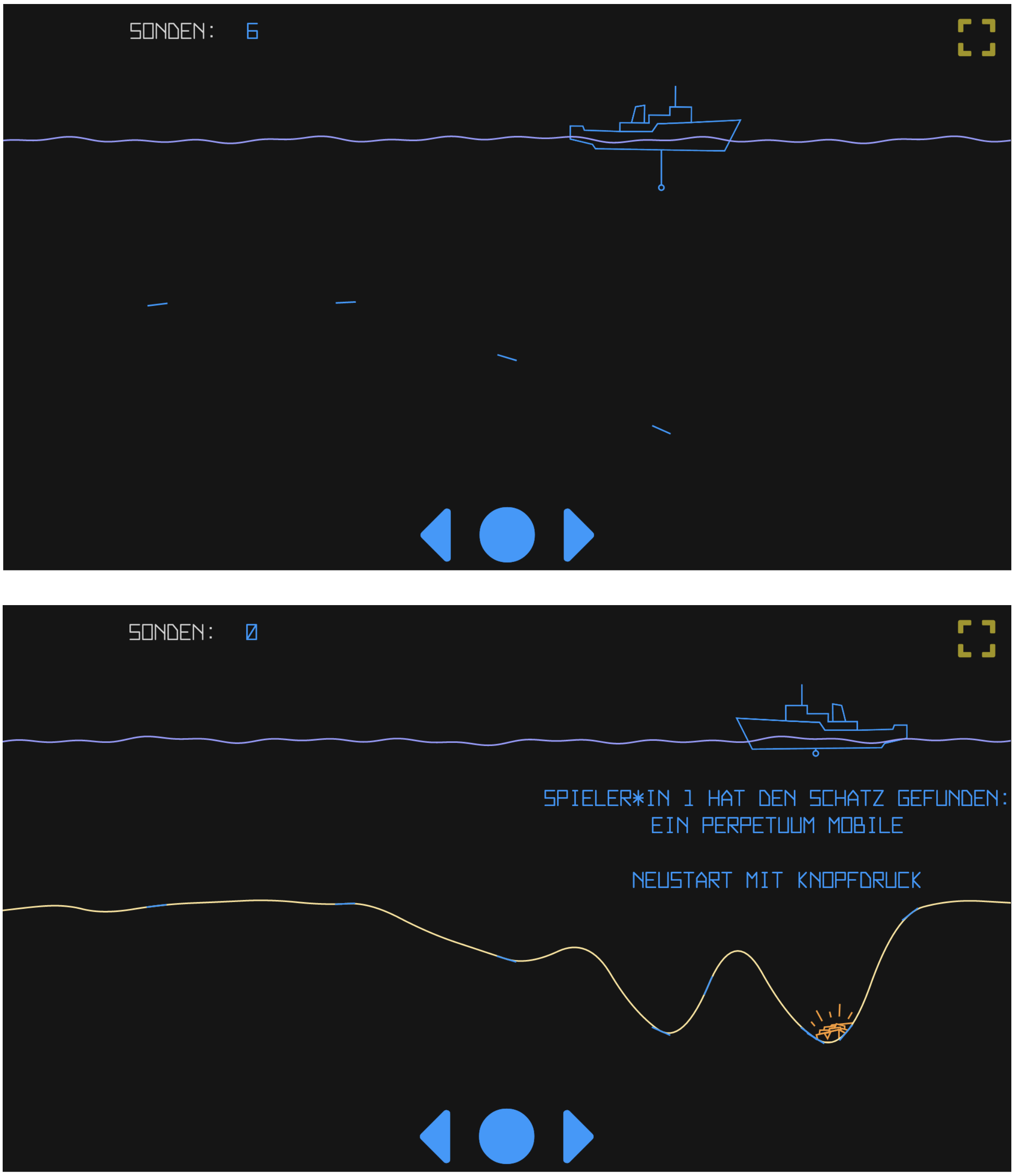


Figure A.3: I

A.3 Transcripts Interviews

We edited the interview protocols for the sake of readability and clarity.

A.4 Interview A: Expert—Physics

I: Okay, also wie gesagt, danke, dass du da bist. Im Rahmen meiner Masterarbeit schreibe ich über ein didaktisches Konzept für neuronale Netze. Zielgruppe sind PhD-Studenten, die aber keine Vorerfahrung haben in dem Bereich. Es aber für ihre Doktorarbeit brauchen - also Anwendung, Umgang mit neuronalen Netzen. Du bist Experte, hast du gesagt?

P: Ja, wenn man es so bezeichnen will, also ich habe schon Erfahrungen damit.

I:Was ist dein Forschungsgebiet?

P: Ich untersuche das Konvergenzverhalten von neuronalen Netzen [00:57.000 —> 01:01.000] und es geht darum quasi, eine physikalisch motivierte Theorie zu entwickeln, [01:01.000 —> wie man das auf einem makroskopischeren Devil beschreiben kann. Ich gucke mir an, wie die Dinger funktionieren.

I: Ja, das ist aber schon mal gut. Genau, für dieses Konzept haben wir uns zwei Seiten angeguckt. Da du jetzt ja Experte bist. schauen wir ein bisschen mehr auf die Kompetenzseite. Es gibt ja noch eine Design-Prinzip-Seite, die betrachtet, was für Spielmechanismen sind dann interessant. Wir werden schon auf die Design Seite eingehen, nur nicht so im Detail. Ich würde mit dir kurz die Kompetenzen anschauen, und dir Zeit geben, das nochmal auf dich wirken zu lassen. Dabei solltest du ein bisschen im Hinterkopf behalten die Leute, von denen wir reden, die haben keine Vorerfahrungen mit neuronalen Netzen, die haben das vielleicht mal gelesen. Du darfst auch schon davon ausgehen, dass es dann auch unterschiedliche Menschen gibt.

P: Darf ich Programmierkenntnisse voraussetzen?

I: So Jein

P: Nein, also keine Angst, den Computer anzufassen, aber ich sage mal, trotzdem den Python 101-Kurs besucht haben.

I: Vielleicht haben sie auch schon mal Python gemacht, aber halt noch nie im Zusammenhang mit NN. Hier auch ein Disclaimer: Das Lern Konzept ist nicht direkt auf einer programmatischen Ebene.

I: [Vorstellung der Kompetenzen]

P: Kompetenzen heißt, was kann ein neuronales Netz?

I: Guter Einwand. Was kannst du, nachdem du das gelernt hast?

P: Ja, ich war mir gar nicht sicher, was das betrifft.

I: Was versuchen wir zu vermitteln?

P: Okay, das heißt, was kann ich erreichen oder was kann ich machen, indem ich das NN verwende?

I: Man nimmt dieses Lernkonzept, das ist keine Ahnung was du tust, und danach kannst du dies Kompetenz.

P: Okay, jetzt verstanden. Du verkaufst mir ein kurs. Das verinnerle ich oder das mache ich, und danach kann ich diese Kompetenz. Das sind am besten Sachen, die ich davor noch nicht konnte.

I: [Vorstellen der Kompetenzen]

P:Am besten sehr modular formuliert.

I: Genau, so atomar wie möglich. [Weiteres Vorstellen der Kompetenzen]

P: [Zu Kompetenz Formalisierung:]Klar, du musst mal natürlich auch irgendwie aussortieren, [06:53.000 —> 06:58.000] was für Leute dann relevant ist und was halt voll egal.

I: Genau. Das sind alles Vorschläge, auf denen dann weiter aufgebaut werden soll, Hier kann noch aussortiert aussortiert werde, wo dann auch mal sagen kann, das ist absoluter Blödsinn, hier fehlt ein großer Baustein. Das ist jetzt auch das Ziel von dem Interview. Du hast jetz Zeit, die Kompetenzen nochmal in Ruhe anzuschauen.

I: [Erklärung Zusammenhang Kompetenz Lernziel und kurze Erklärung Lernziele]

P: Was hast du dir bei der, also Roll-of-Data gedacht?,

I: Das ist halt vor allem ein sehr großer Punkt des Themas.

P: Ja, also ich, das, ja, geht da dann auch immer direkt darum on, ob Daten vollständig sind oder unvollständig? Worann kann es liegen, dass es nicht funktioniert? und so weiter. Also nicht ganz so einfach.

I:Aber im Prinzip geht es da darum, was du gesagt hast. Also ich muss erkennen, wie wichtig die richtigen Daten für meinen Ergebnis nachher sind. Das ist der Kerngedanke.

P: Ich meine, wenn du schlechte Daten hast, kannst du nicht erwarten, das zaubert.

I: Und dann halt auch Ursachen ausmachen, also wenn ich den falsches Label vergeb, dann ist gerade das halt falsch ist.

P: Ja, also klar, ich meine, wenn du sie selber Label vergibst, und jedes zweite Label unpassend ist, dann geht das schief. Nee, okay, ich verstehe. Ich denke, ich bin warm geworden.

I: Fällt dir hier was auf?

P: Also, inwiefern fällt mit was auf

I: Entweder hier ist noch eine sehr große Lücke. In dem Themenbereich, da fehlt noch wirklich ein Kompetenz. Oder ohne diese Kompetenz geht es nicht oder es ist schon auch wichtig. Oder auch was, wo du sagst, ist vielleicht überflüssig. Für einen PhD-Studenten nicht interessant an der Stelle.

P: Also, es kommt darauf an, auf welchem, ich finde, wenn ich stelle mir jetzt irgendjemand vor, der oder die, hat einen Datensatz generiert und möchte jetzt da quasi eine Klassifizierung durchführen und da einfach schauen: okay, was steckt da drin? Dann wäre jetzt so, wenn ich jemand sagen würde: also wenn jemand mich fragt, was soll ich da tun? Ich habe keinen Plan. Dann sage ich, schau dir die zwei, drei Beispiele an, die du auf, zum Beispiel, TensorFlow findest.

Und dann ist nimm dir ein example neural network für classification, [11:48.000 —> 11:52.000] dann würde ich sagen, kopier dir einfach das Ding,

guck dir das an und probier das mal anzuwenden. Ich finde, es ist immer ein riesiger Schritt von, wenn du jetzt ein neuronales Netz auf was an, zu, ich habe jetzt das beste neuronale Netz für meinen Fall. Und ich bin mir auch nicht sicher, ob Personen, die das einfach nur machen wollen und sich da jetzt nicht zu viel damit auseinandersetzen wollen, weil die Materie, das Feld ist riesig.

Ich weiß nicht, ob die sich damit beschäftigen müssen, ob jetzt Sigmoid oder Reliu function für sie das Richtige ist. Also, das zu wissen, was es ist, ist wichtig. Aber ich weiß nicht, ob das denen was bringt. Also, ich glaube, denen würde es mehr bringen, wenn sie zum Beispiel wissen, was ist ein Dense NN?

I: Also, Typen?

P: Genau, Typen von neuronalen Netzen. Wenn es dann um die tatsächliche Struktur geht, würde ich sagen Google, such nach was, wo Leute so was gemacht haben [12:53.000 —> 12:55.000] und copy-paste das einfach. Und dann guck dir an, da gibt es richtig coole Tutorials dazu, [13:00.000 —> 13:03.000] wie man strukturell vorgehen muss, um das beste neuronale Netz zu finden. Zum Beispiel jetzt die 0815 herangehensweise ist, ich nehme ein kleines Modell und das mache ich dann Stück für Stück größer. Weil wenn ich mit einem zu großen Modell starte, dann braucht das viel zu lang und manchmal ist die Komplexität bei deinen Daten gar nicht gut. Deswegen startest du mit was Kleinem und baust es auf. Für Classification hätte ich eh gesagt, Activation Function ist also der ganz dumme Standard, einfach Relu zu verwenden. So, ich meine, das ist cool für die, wenn sie wissen, was das macht und wie das funktioniert. Aber ich weiß nicht, ob du das Verständnis entwickeln kannst für wie die Relu-Activation jetzt im Vergleich zu einer Sigmoid-Activation dein Lernverhalten ändert oder was das dir bringt. Das ist selbst, also selbst. . .

I: Ja, das ist komplex.

P: Die Leute, die richtig krass damit arbeiten, ist das nicht immer also vollständig klar, warum jetzt das so viel besser ist oder so. Da gebe ich dann noch kurz eine Zusatzinfo. Und zwar ein weiteres Ziel von dem Spiel, ist, dass du halt den Menschen, den Werkzeug mit an die Hand gibst. Du sagst, ich habe ein sehr grobes Basisverständnis, das ist so der kleinste gemeinsame Nenner für verschiedenste Leute. Und mit dem Wissen können sie dann sagen, an der Stelle brauche ich mehr Information und dann lese ich mir Paper durch dazu. Und dann verstehe ich das Paper, weil ich dieses Spiel gespielt habe. Geht vielleicht auch ein bisschen in die Richtung jetzt.

I: Du bist jetzt auch bei den Formalisation-Teilgrad gewesen, oder?

P: Ja genau. Also, also vielleicht fangen wir mal ganz vorne an. Du steigst eine mit, was neuronalen Netze sind, das ist wichtig. I: Ganz kurz, die Kompetenzen sind nicht chronologisch angeordnet. Auch durcheinander die Lernziele. Das ist nicht, du bringst nicht eine Kompetenz bei und dann die nächste, und da werden dann vielleicht drei Sachen auf einmal beigebracht. So ein intuitives Matheverständnis und gleichzeitig lernen wir noch den Begriff Neuron dabei.

P: Was mir auf, also ich meine, das bewegt sich ja ungefähr, also so wie ich die Struktur verstanden habe, ist zumindest die ersten zwei Punkte. Sind strukturelle Größe, also das (Strength and Weaknesses) da ist Verständnis allgemein um quasi das Thema einzugliedern. Das zweite ist strukturelles Verständnis (NN Structure) von dem Thema selbst.

I: Ja, von den Begrifflichkeiten.

P: Genau von den Begrifflichkeiten, dass du weißt, also erst mal, [15:44.000 —> 15:46.000] ich habe das neuronalen Netz als Ganzes, wie liegt es im Themenbereich und danach gucke ich rein. Dann kommt Dynamik, wie funktioniert lernen und dann kommt halt, okay, ich muss natürlich auch, also Daten und so weiter. Ein bisschen variabel.

I: Du kannst es aber auch anders anordnen z.B., ich bringe zuerst bei, wie wichtig Daten sind, bevor ich mir angucke, wie sieht das neuronalen Netz genau aus.

P: Ich finde, also was mir zum Beispiel brutal geholfen hat, ich habe einen Anfängerkurs in Schweden besucht für Nn Also ich kannte mich schon ein bisschen aus. Und dann habe ich mir gedacht, ich mache einen Anfängerkurs in Machine Learning, weil ich hatte schon Ahnung von neuronalen Netzen und ein paar anderen Methoden, aber was ich da richtig cool fand und was mir echt viel geholfen hat, um überhaupt zu verstehen, was mache ich eigentlich, ist zu wissen, wo neuronalen Netze, also, dass es mehrere Machine Learning Methoden gibt und neuronalen Netze quasi nur eine der Anwendungen sind. Und dann zum Beispiel so Begriffe klären, wie was ist Deep Learning? Ab wann ist etwas Deep? Also wann ist es ein Deep-Neuronal Work und was ist der Unterschied? So, dann so Begriffe einführen, wie was ist eine Blackbox, was ist eine Whitebox? So, warum sind die so gut? und warum verwendet sie trotzdem nicht jeder? Und so weiter.

I: Und so mehr Kontext schaffen?

P: Genau, dass man den Kontext hat, weil ich finde, das ist fast wichtiger zu wissen, was tue ich eigentlich gerade, in welchem Bereich bewege ich mich und was gäbe es denn, dass du mal von Alternativen gehört hast, wie das es einfach heißt, okay, ich mache. Ich weiß es so, ich als Nichtwissenderdenke, ich mache jetzt Machine Learning und künstliche Intelligenz und dann spiele ich dein Spiel. Und dann denke ich so, [17:32.000 —> 17:34.000] künstliche Intelligenz, neuronale Netze. Aber ich habe dann nicht die Weitsicht und ich finde das fast wichtiger, Leuten ein bisschen weitblick zu geben und zu sagen, das ist jetzt eine Methodik. Es gibt viele, die ist bekannt, weil, die ist nicht so beliebt in manchen Aspekten, weil.. dass sie wissen, okay, das passt jetzt für mich, ich will das benutzen, aber wenn das für mich nicht passen sollte oder irgendjemand anders, den ich kenne, dann habe ich verstanden, wann man das benutzt. Und ich finde, das ist sehr essenziell. So, und wenn die Person dann weiß, okay, neuronale Netze ist ein gutes Ding für mich, dann lohnt es sich zu lernen, wie funktioniert es, was macht es.

I: Was gibt es da noch mal in Detail, was für Unterschiede?

P: Genau, wie funktioniert es, wie wenn nichts an? Und dann das Verständnis, das Verstärkung.

I: Was ist für dich anwenden? Heißt es, ich habe ein Netz und muss es nur noch trainieren? Heißt es, ich habe ein neuronales Netz, ich muss es anpassen, muss vielleicht noch mal in den Code reinschauen?

P: Also beim Anwenden gibt es für mich zwei Stufen, es gibt Stufe 1, ich entscheide mich für eine Architektur und Stufe 2 ist ich trainiere es. Und die Architektur hängt noch mehr mit den Daten zusammen, als das Training selbst. Im Training selbst gibt es so ein bisschen Daumenregeln, die man machen kann, und dann läuft es schon irgendwie. Für sich, für eine Architektur entscheidend, ist schwierig, und das ist auch das, also. . .

I: Was genau meinst du mit Architektur?

P: Architektur heißt, ich entscheide mich dafür, wie tief ist mein neuronales Netz gekreiert, I: Also anzahl Layer . . .

P: genau Layer, welche Activation Functions und so weiter. Ich meine, das definiert man, und das ist fix, und dann trainiert man das. So, und dann guckt man, wie gut es ist. Und jetzt kann es halt sein,ich meine, wenn ich das viel zu klein wähle, ist gehts schief.

I: Das heißt, beim Anwenden gehört aber für dich auch noch das Festlegen von der Architektur mit dazu.

P: Genau, das ist Schritt 1. Schritt 1, Architektur festlegen, Schritt 2 quasi Training machen. Und das Problem, dass ich sehe, wie weit will man Leuten beibringen, die Architektur zu wählen. Das Training selbst zu machen, ist okay. Ich meine, in den meisten APIs ist es einfach... enau, train model, und in die Funktion train model steckst du dann noch dein Optimizer rein.

I: Und was die dann genau macht, versteht dann sowieso niemand P: [19:58.000 —> 20:00.000]

P: Genau, das ist dann egal. Dass man weiß, dass es über gradient descent trainiert, [20:02.000 —> 20:04.000] ist cool, so, dass man überhaupt weiß, wie das funktioniert, dass man ein Gefühl dafür hat, [20:06.000 —> 20:08.000] das macht das, das ist nicht komplett komisch für einen, wenn man da train model, und dann macht es magische Sachen. So die Magie zu nehmen, ist wichtig. Ich weiß nur nicht, wie weit man Leute dazu... Wie schnell man Leute da hinführen kann, dass sie wissen, wann ich jetzt was benutze, welche Architektur und welchen Typ von neuronalem Netz und so weiter, [20:28.000 —> 20:31.000] vor allem welche Architektur, ist glaub ich echt knifflig. Ich hätte gesagt, bevor ich Leuten beibringen, wie viele Layers sie brauchen, dass sie ein Gefühl dafür haben, [20:38.000 —> 20:41.000] wie viele Layers sie wohnen nehmen müssen und so, hätte ich gesagt copy-paste von Sachen, die funktionieren. Also ich glaube, ich fände es cool, wenn die Leute das wissen, wenn sie verstehen, was sie machen, aber gar nicht so... Also im Detail schon cool aber zumindest, dass... dass man Verständnis dafür hat, wo bewege ich mich. Das fände ich cool. Also klar, ich meine, Learning ist wichtig, dass man weiß, was gradient descent algorithm ist, was eine Cost Function ist und so, das ist essentiell. Struktur von NN Das ist der Punkt, wo ich sage, da bin ich mir nicht sicher. Also was ist ein Feedforward Network? Was stand da nochmal alles (Learn Goal NN Learning)

I: Also da ging es so ein bisschen um den Ablauf, dass man sich vorher gemeint hat mit dem, wie laufen die Daten, weil wir halt auch Feedforward den Fokus legen in so einem... Wie bewegen sie sich da?

P: Ich meine, dass sie einmal von hinten durchgehen und dann eine Representation kriegt und auf der dann... Aber ich weiß gar nicht, ob die das wissen müssen. Das kommt auch auf die Library an, die du verwendest. wenn du zum Beispiel TensorFlow nimmst und da Keras importierst, also mit TensorFlow irgendwie arbeitest, mit der easy to do Library, dann hast du den Vorteil, dass du wirklich einfach... Du guckst dir, das sind drei Zeilen. Und die Zeile ausführen ist einfach train model und wenn du da keinen Optimizer reingibst, dann nimmt der einfach den Standard Adam Optimizer so, du musst da nichts für machen. Das geht wirklich direkt. Du musst kein Wissen darüber haben, wie das funktioniert Wenn du zum Beispiel jetzt PyTorch arbeiten willst, was dir ein bisschen mehr Flexibilität bietet, dann musst du deine Architektur, also dein Netzwerk wirklich selbst bauen.

I: Also da ist halt auch wieder problem pezifisch.

P: Genau, das ist viel spezifischer. Also mit PyTorch kannst du... Also TensorFlow, Keras und die ganzen Sachen, die sind wirklich hauptsächlich auf Anwendung ausgelegt. Hätte ich jetzt gesagt, also wenn du die fragst, sagen die dir bestimmt was anderes, meine Erfahrung sagt, dass es Libraries gibt, die auf Anwendung zielen und Libraries, die auf Anwendung und quasi Flexibilität zielen. Und da gibt es noch ganz experimentelles Zeug, das benutzen wir hier. Das ist Libraries, du musst alles selber machen. Also alles, alles.

I: Warum gibt es da noch eine Library?

P: Genau, also das einzige Sinn dahinter ist, dass du quasi die Beschleunigung, also

I: dass du quasi auf einer GPU arbeiten kannst und das nativ darauf laufen kann. Das ist das Einzige. Aber sonst programmierst du es quasi in Numpy, doof gesagt. Also alles wirklich selbst. Deswegen bin ich mir nicht sicher. Intuitiv hätte ich den Fokus mehr auf äußeres Verstandnis gelegt und weniger auf innen drin.

I: Also auch ganz klar top down.

P: Genau, ganz klar top down. Weil auch so wie ich Sachen beigebracht bekommen habe, dass sich für mich richtig angefühlt hat, das so zu lernen.

I: Ja, macht ja auch Sinn, das erstmal einordnen zu können in das gesamte Feld.

P: Und ich meine dann, wenn Leute, also wie funktioniert denn das Spiel?

I: Genau, das wollte ich dir jetzt gerade fragen. Hast du die Zeit noch?

P: Ja, klar.

I: Dann gehen wir kurz über die Design Prinzipien.

I [Kurze Vorstellung Design Prinzipien]

I: Spielst du Spiele?

P: Nein, gar nicht.

I: Okay, jetzt spielst du Brettspiele?

P: Geht. Ich bin kein Spieletyp.

I: Lass uns trotzdem die Einschätzung machne:

I: [Vorstellung Spielertypen]

P: Ich denke, ich wäre zwischen Ich fühle mich nicht. . .

I: Killer ist einfach ein dummes Wort, das muss man da ganz ehrlich sagen. Killer ist es einfach nicht so smart gewählt, aber. . .

I: Ich hätte das Competition oder so genannt

P: Kompetition schon wichtig, aber auch die Möglichkeit, nicht Kompetition zu haben für mich Also, beide Sachen. Das ist. . . Also, muss ich mich für eins entscheiden?

I: Nein, nein. Und so in Bezug auf Lernspiele, wärst du auch so in die Richtung. Also, so duolingo-mäßig ist ja schon eher so ein Achiever. Oder lernst du lieber, wo du ausprobieren kannst oder in den Forum hast. P: Wenn ich jetzt einen Kumpel hätte, der mit mir das gleichzeitig anfangen würde, würde mir das brutal helfen. Ich weiß nicht, ob mir jetzt einfach irgendjemand ohne Bezug hilft. Also, wenn ich quasi weiß, oh, guck mal, gerade hat auch einer angefangen, aber den kenn ich nicht, dann ist mir das, glaube ich, egal. Also, da würde ich halt das Kompetitive sehen, aber wenn dann nur auf der persönlichen Ebene. Und sonst wäre ich komplett bei Achievers.

I: Also, so ein bisschen Killer, aber nur mit guten Freunden.

P: Genau, Killer, aber nur mit guten Freunden.

I: Und dann haltet Acievements. dann stelle ich dir kurz das Spiel vor, []Stellt Speil vor .

P: [coole Idee zur Gradient Descent Spiel

I: [Vorstellung Spielideen]

P: Ja, ist cool.

I: Und da könnte man auch Achievments für Challenges sammeln, messen kannst, dich mit anderen Leuten und Progress und keine Ahnung.

P: So wie 3 Tage am Stück gelernt und so

I: Genau. Und dass du halt hier auch nochmal eine andere Ebene von Progress-Indikator hast. Dass du zum Beispiel sagst, warum ich interessiere nur Anwendungssachen und es gibt halt eine Kategorie von Spielen, die nur anwendungsbezogen sind, dass das alles grün ist hier drinnen, dass du dann halt siehst, ich bin im Anwendungsbereich so weit fortgeschritten, aber mir fehlt es halt jetzt in der Struktur irgendwie, oder irgendwie so, dass du da halt eine mehr dimensionale einen Progress hast. Das ist so dieser Mountain of Knowledge.

P: Cool.

I: Genau. Und dzu den Kompetenzen würde mich interessieren: Ist das so angebracht, die Kompetenzen beizubringen? werden Kompetenzen ausreichend abgedeckt. Du merkst, pro Spiel wird nicht nur eine Kompetenz vermittelt, sondern es ist verwoben. Findest du den Ansatz gut und angemessen für PhD-Studenten. Und sonstige Anmerkungen.

P: Also, ich finde, bei manchen Beispielen, die du gesagt hast, sehe ich es voll, da macht es richtig Sinn. Bei anderen weiß ich nicht, ob das, also wenn ich das richtig verstanden hab, dann baust du hier quasi deinen Neuron, also halt dein Netzwerk, genau, dass du den Netzwerk baust. Verstehe ich, ich weiß nur nicht, ob der, also, ich mein, jedes Spiel hat doch bestimmt so eine, oder jedes von den Ideen muss doch eine Anwendungszeit und quasi Wissensbildungsratio folgen. Also, ich mein, wenn du eine Sache 10-mal wiederholst, die du instant verstanden hast, dann hast du ja kein Bock mehr drauf. Und ich glaube, das ist dass sowas schwierig sein könnte. Also, dass du vor allem dir dann auch richtig viel Mühe gibst, das zu coden, am Ende, und das zu erstellen, und dass ja mehr Wert den Leuten dann davon haben, nicht so viel ist. Aber andere Sachen fand ich richtig cool. Also, zum Beispiel das, das mit dem Abgrund und der Funktion, das fand ich sehr geil. Das fand ich richtig cool. Ich glaub, so kann man richtig geil Funktionen lernen. Das macht voll Sinn.

I: Also, bei dir ist auch dann ihr so, gucken, was die Leute wirklich wollen, was sie wirklich brauchen.

P: Ich glaube, also ich kann mir vorstellen, dass es echt schwierig ist, viele kleine Spiele zu machen, und jedes Spiel hat das richtige Maß. Das glaub ich richtig hart. Also, das Maß da zu finden, knifflig. Sowas finde ich richtig cool.

I: Und du musst ja auch immer dran denken, das ist das, was ich mit dem Mechanismus eine gute Spielidee. Oder muss man halt wirklich viel, das ist nämlich das, wo ich drüber geschaffen bin. Uff, wie bringe ich jetzt sowas bei?

P: Ja, ist so. Das ist schon hart. Also, wenn es halt für PhD ist, dann darf es auch nicht zu plump werden, was auch nicht so einfach ist. Weil ich finde, gerade mit Spielen, das ist deutlich leichter in einem 10-Jährigen, was vermitteln zu wollen, weil. . .

I: Das ist ja noch mehr Spaß dran, um rumklicken.

P: Genau. Der PhD-Student ist halt so. . .

I: Ziele gerichter.

P: Aber an sich, coole Idee. Also, finde ich eine gute Sache, dass man Leuten versucht, das so beizubringen. Find ich sehr cool, weil nicht jeder hat Bock, irgendwelche, keine Ahnung, Blocks durchzulesen.

I: Ja, und wie gesagt, die Idee ist ja, dich in dem Paper nicht mehr verloren fühlst, wenn du halt mal so ein Mathematisches Paper liest. Würdest du sagen, es macht halt einfach mehr Sinn für PhD-Studenten, was man halt schon kennt, diese Kurse zu haben, wie Udemy zum Beispiel, mit einem Text hast, unterbrochen von einem Spielchen. Und dann mit einem Text, mit einem Spielchen oder einem Video. Also, dass du halt eher dieses Online-Kurs lernen hast] im Vergleich zu einem Spiel.

P: Ja, sehe ich.Ich würde das schon so machen. Also, ich persönlich würde quasi Informationen in Form von Text oder Bildern, gepaart mit Spielen und Spiele dann zielgerichtet dort einsetzen, und quasi das Verständnis nicht instant kommt, sondern das Verständnis generativ entwickelt werden muss. Und quasi die Punkte sind, wenn ich jetzt durch irgendwie eine Anleitung gehe, wo ich sage, das raff ich nicht, dass das durch Spiel vermittelt wird.

I: Jetzt nur auf PhD-Studenten mit so, oder auch für jüngere Gruppen?

P: Ich glaube, es ist schon eher auf älteren. Also, ich weiß halt nicht, ältere Leute sind, können sich länger am Ball halten, und quälen sich auch mehr durch den Text durch. Und wenn man die dann erlöst, kurzzeitig, geht das voll klar. Jüngere Leute, glaube ich, verliess so schneller. Du müsst quasi die Frequenz an Spielen erhöhen, so.

I: Und dann bist du ja schon fast bei unserer soielidee.

P: Genau, dann bist du da.

A.5 Interview B: Expert—Chemistry

I: Genau, also um dich abzuholen, ich schreibe meine Masterarbeit über ein Lehrkonzept.

Das Konzept soll spielerisch das Thema neuronelle Netze behandeln.

Als Zielgruppe sind angedacht PhD-Studenten, die anfangen und noch keinen Vorwissen in dem Gebiet haben, es aber für ihre Arbeit gebrauchen können.

Das Konzept besteht aus Kompetenzen und dann Design-Ideen.

Und da würde ich jetzt erstmal fragen, so vom Einschätzen her, dein Könnensstand, dein Wissensstand, du hast schon ein bisschen Ahnung von neuronellen Netze, vermute ich.

P: Ja, ich hoffe ja. Es gibt immer wieder neue Sachen, aber ja.

I:Okay, was ist dein Themengebiet?

P: Neuronelle Netze für, also Regressionsmodelle, für Energien.

I:Ah, okay. Und du hattest Chemie studiert?

P: Ich hab ursprünglich Chemie gemacht, mache dann jetzt halt [meinen Doktor] in Computerphysik.

I: Und der Wechsel hat funktioniert?

P: Tatsächlich, ja.

I: [Okay, da du ein bissche Ahnung hast würde ich kurz mit dir über die Kompetenzen gehen.

Und bevor ich dich dann die Fragen dazu stelle, gebe ich dir ein bisschen Zeit dich einzulesen

I:[Vorstellung der Kompetenzen]

P: Wie genau läuft das dann ab? ist das, wird das nacher gezeigt? Oder was für Feedback möchtest du bekommen?

I: Genau, ich frage dich nachher so ein bisschen zum Inhalt der Kompetenzen.

P: Okay, ich bin mal gespannt.

I:Also hier neben den Kompetenzen ist der Block mir den Design Prinzipien, der für uns nebensächlicher ist, weil wir uns auf die Kompetenzen fokussieren. Das heißt, da gehen wir nur relativ schnell drüber, damit sind fünf Design-Prinzipien, die wir dann rausgestellt haben damit du ein vollständiges Bild bekommst.

I :[Vorstellung der Designprinzipien bis ca 07.38]

P: Geht das Prinzip Interaktion so ein bisschen in die Richtung Adaptives Lernen, z.B. bei Brilliant oder so anderen Plattformen in der Richtung?

I: Ja, ein eine kleine Spur darüber. Also, wir haben uns überlegt, dass es schon relativ viele Kurse in die Richtung gibt, die Gamification verwenden - also die ein Kursmodul haben, in dem immer wieder ein Spielchen zwischendrin vorkommt oder ein Quiz oder ein Puzzle, was du lösen musst. Wir wollen unser Konzept ganz als Spiel verpacken. Wie das mit der Story und so witer funktioniert, erkläre ich dir gleich. Aber die Kernidee ist wirklich ohne große Unterbrechungen in einem Medium zu bleiben.

P: Okay, also quasi nicht abwechselnd Lernen, Fragen.

I: Genau, integriert. Bevor wir jetzt weitermachen erstmal, würde ich dich einem Spieltyp zuordnen Vielleicht kennst du diese Unterteilung schon. Spielst du denn spiele?

P: Ja, hin und wieder.

I:[Erklärung der Spelertypen]

I: Versuche dich mal so eine ungefähr einzuschätzen oder auch vielleicht anzugeben, was du überhaupt gar nicht bist.

P: Das finde ich schwierig, weil von allem irgendwie etwas zutrifft. Vielleicht am ehesten in Richtung Explorers so ein bisschen, aber ich kann es wirklich schwer sagen.

I: Ist was dabei, wo du sagst, da siehst du dich irgendwie gar nicht wieder? Oder gibt es eine Eigenschaft von den anderen Spielertypen, die den Auschlag bist, dass du der Typ nicht bist?

P: Schwierig. Ich sehe überall Dinge, die halt interessant sind. Ich meine, bei einem Spiel, das mal alleine spielt, hat man keinen Socialize-Faktor. Wenn ein Spielers online mit anderen spielt, geht es nur umd diesen sozialen Faktor und dann am besten noch im Chat mit anderen.

I: Aber würdest du jetzt eher einen Spiel spielen, wo ein Chat hat? Bist du eher jemand, der mit Freunden dann spielt oder lieber alleine?

P: Beides. Während Corona spielt man viel mit anderen zusammen online. Irgendwie, da gab es ziemlich gute Spiele mit Among Us oder sowas, was wir immer wieder gespielt haben. Aber auf der anderen Seite, wenn ich irgendwie zu Hause sitze oder so, dann ist es leichter mal selber kurz abzumachen. Sorry, da habe ich irgendwie... Tenenz zur Mitt so genau. Kannst mich irgendwo so da... Ja, so mit World Interacten.

P: Ich meine, ich bin aber Explorer und ein Killer schließt sich eigentlich nicht aus. Das wäre fast das, wo ich mich am ehesten sehe, mit zu sagen, okay, ich erkunde gerne, und wenn ich was gefunden habe, dann möchte ich das aber auch gut vollenden. Aber das existiert halt da auf der Diagonale. Man muss noch so eine Weitere Dimension hinzufügen.

[Kurze Diskussion über das Diagramm]

I: Dann reden wir jetzt erstmal über die Kompetenzen Ist dir was aufgefallen, wo du dir gedacht hast, da das fehlt mir jetzt aer richtig?

P: Also fehlt mir richtig, würde ich nicht sagen. Aber ich mache sehr viel Supervised-Learning. Also der Un-Supervised-Teil, der geht jetzt in meiner Forschung ein bisschen unter. Weil ich halt eigentlich nur gelabelte Daten habe.

I: Wenn du jetzt so ein bisschen überlegst, dass du ganz am Anfang bist, mit dem Wissen, dass du jetzt hast, was wären da so die wichtigsten Punkte, die du lernen... musst, um praktisch mit deiner Arbeit weiterzumachen?

P: Noch mal bitte.

I: Also stelle vor, du weißt noch nichts von Neuronalen Netzen, aber du hast das gleiche Thema, das du jetzt bearbeitest. Was wären so die ersten Punkte, die du verstehen müsstest, um halt gut arbeiten zu können?

P: Also was mir von der Theorie am Anfang sehr viel geholfen hat, war immer zu sehen, ich kann quasi die Mathematik fast eins zu eins übersetzen, weil ich sage, okay, ich brauche die Ableitung von irgendwas. Das heißt, ich mache einfach die Ableitung von meinem neuronalen Netzwerk nach dem und dem oder sowas in Richtung, was bei uns relativ wichtig ist. Also gerade das Prtinzip der automatic differentiation ist relativ wichtig. Und auch, wie man sich eine Losfunktion zusammenstellt, dass man quasi sagt, okay, die Teile optimiert man. Die Netzwerke, die ich nutze, sind in dem Fall erstmal relativ langweilig, weil es einfach nur dense neural networks sind.

I: Also du wendest an?

P: Ich wendest ja an, ja.

I: Wie würdest du jetzt anwenden von neuronalen Netzen beschreiben?

P: Gut, in meinem Fall ist es tatsächlich quasi ein Surrogate-Model. Also ich habe was, was ich rechne, was sehr langsam ist und darauf trainiere ich was und dadurch mache ich halt den Prozess quasi 10.000, 100.000 mal schneller.

I: Okay, also du trainierst praktisch und wendest an das trainierte Netz an, du hast noch kein vorainiertes Netz.

P:[Ich habe noch kein vortrainiertes Netz, genau. Das ist die Anwendung, die ich habe.

I: Musstest du auch Sachen ändern in dem neuronalen Netz?

P: Gut, also ja, die Parameter sind natürlich sehr flexibel, was für Activation Functions man hat, wie die Struktur vom Netzwerk aufgebaut ist. Aber im Großteil sind es wirklich nur Layers und was für uns auch sehr wichtig ist sind die Inputdaten. Wir kommen quasi aus dem Raum von kathesischen Koordinaten, wollen aber dann in den Raum von [15:00.000 —> 15:02.000] Sachen, die Translationsinvariant sind, die Rotationsinvariant sind und die Paramutdationsinvariant sind. Das heißt, diese Transformation ist wichtig, gerade von den Trainingsdaten, was auch mal kurz beschrieben hattest. Also wie wählt man sinnvolle Trainingsdaten aus? Quasi zu sagen, okay, ich will nicht, dass mein Netzwerk diese Invarianzen in den Daten lernt, [15:18.000 —> 15:20.000] sondern ich kann es dem Netzwerk schon einfacher machen und als Vorne rein sagen, okay, ich baue diese Invarianzen in die Trainingsdaten ein.

I: Dann gehen wit nochmal von vorne über die Kompetenzen: Bei den stärken Schwächen st es ausreichend, in dem, wie wir das behandelt haben, würdest du sagen, man braucht da mehr den ethischen Aspekt drinnen und man hat ein bisschen Problemstellungen kennt. Oder setzen wir bei Ph.D. Studenten voraus, dass sie schon Aussagen von neuronalen Netzen kritisch betrachten.

P: In meinem Fall ist die Ethik komplett langweilig, weil wir machen nichts mit Menschen. Auf der anderen Seite finde ich, wenn man was mit Menschen macht, ist die Ethik schon relativ wichtig. Man hat halt nachher eine Lossfunktion oder ein Netzwerk, das man optimiert. Und wenn das halt auf irgendwas hinoptimiert, das ethisch fragewürdig ist, ist das schwierig Ich finde es sehr themaabhängig. In meinem Fall Ethik komplett irrelevant.

I: Dann Struktur, also dieses Aufbauwissen, was in einem neuronalen Netz drinnen ist, fehlt dir da was? Habe ich da irgendwas übersehen? Keine Ahnung, ich habe Basisbegriffe jetzt genommen, die es gibt. Wenn man halt diese typische Visualisierung hat von dem neuronalen Netz, also deiser Graph dass man die Komponenten erklären kann, das ist so ein bisschen das Ziel.

P: Ja, doch, also ich glaube, war alles da - Nodes, Weights, Biases. Activation Function habe ich glaube ich nicht gesehen. Ja, die habe ich so ein bisschen, das war so ein Zwischending für mich, zwischen Lernen und Struktur,

I: Aber auf jedenFall: Activation Function wichtig?

P: Ja, und vielleicht auch der Unterschied vielleicht ein bisschen zwischen Regression und Klassifizierung.

I: Also so verschiedene Problemtypen, für die das angewendet werden kann.

P: Also das sind zumindest bei uns so diese beiden großen Typen, dass man sagt, man hat ein Regressionsmodell, und man hat halt ein Klassifizierung Modell. Also ein Klassifier, und da ist dann halt mit einer Softmax Funktion am Ende schon wichtig, was für den Activation Function man da drauf hat. Das ist ein Beispiel, das man Wahrscheinlichkeitsverteilung am Ende rausbekommt, aber das ist schon sehr spezifisch deswegen.

I: Hättest du am Anfang eine Frage gehabt, die du direkt gerne direkt beantwortet bekommen hättest, und die dir viel weiter geholfen hätte? Oder hattest du auch schon ein Vorwissen zu neuronalen Netzen?

P: Ja, tatsächlich, meine ersten neuronalen Netzwerke kam aus dem Bereich Heimsteuerung. Ich habe sehr viel mit Anwendung angefangen. Ich habe mich gemacht, da war so ein Datensatz zu trainieren, und zu überlegen [18:12.000 —> 18:14.000] jetzt habe ich halt dieses Modell - Wie kann ich dieses Modell anwenden? Das waren natürlich die Sachen, die mich immer interessiert haben. Wie packe ich da jetzt meinen eigenen handschriftlichen Buchstaben rein, dass der erkannt wird? Das fand ich am Anfang relativ herausfordernd, aber ich habe mich auch nicht so viel für die Mathematik interessiert. Ich habe halt einfach den Code runtergeschrieben ich schreib diesen Code runter.

I: Für dich war es auch praktisch so, ich gebe was rein, es kommt was raus und zwischendrin ist Blackbox.

P: Genau, das ist das wo ich hergekommen bin. Mittlerweile sehe das natürlich anders. Gut, die Blackbox ist immer noch da. Aber so habe ich mich an das Thema beschäftigt.

I: Würdest du es anders machen im Nachhinein?

P: Nein, ich glaube nicht. Aber das liegt vielleicht auch ein bisschen am Chemiestudium, ich habe das Gefühl, da ist man sehr viel explorativ unterwegs und schmeißt einfach Sachen zusammen und guckt, was rauskommt.

I: Aber ich glaube, das sind viele bei dir.

P: Es gibt unterschiedliche Ansätze. Das geführt gerade hier auch zum Beispiel einige aus dem theoretischen Physikbereich, die dann eher von der Mathematik kommen und die Anwendung später dazu bringen. Dann hart in die MML-Theorie gehen und gucken, was da passiert.

I: Wenn du sagst, Kompetenzen sind abgedeckt bei dir, dann würde ich unseren Hamster vorstellen.

P: Ich bin gespannt.

I: [Vorstellung Spiel Idee]

P: Also das mit den lveln woe das Mario Spiel quasi so ein bisschen.

I: Ja, so ein bisschen in die Richtung. Genau. Und hast du Fragen dazu, Anmerkungen oder Feedback?

P: Ja, ne. Also das sind Neuronale netzwerke sinnvoll, ans Ende zu packen. Gut, ich meine, wenn man nicht weiß, was sie machen, kann man auch schlecht über Vor-und Nachteile reden.

I: Man kann es natürlich auch high-levelig machen, dass man eine Einführung hat und sagt, es gibt Maschinen, die über Menschen entscheiden, dann kann man. . .

Für mich war der Fokus dann ein bisschen mehr drauf gerade, wie du meinst mit dieser Blackbox, die man halt nach wie vor hat. Also wenn du genaue Zahlen draußen ist halt Neuronalesnetz nichts für dich, weil es dann halt nur mit einer Wahrscheinlichkeit diese genaue. Zahlen hinten rauskommt. Für andere ist es so, ich gebe was rein, es kommt was rein und mehr muss ich nicht wissen. Das heißt, da muss man auch wieder über die Ebene diskutieren, Dann reden schauen wir uns Mal die Mechanismen an: Dazu muss ich noch sagen, das es ist jetzt halt eine Vorstellung ein Konzepz von einem Spiel, das man verwenden könnte, auf eine Art von Kompetezn/Problem das man vermitteln möchte.

Also das ist jetzt nicht spezifisch zugeschnitten auf ein bestimmtes Szenario sondern ein Konzept und eine grobe Idee.

I: [Vorstellung Meachnismen]

P: [Zum Artbot: Das ist eine coole Visualisierung.

I: [Vorstellung Meachnismen]

I: Das sind so die Konzepte, die wir dazu haben. Und da ist natürlich eine Aufgabe, die in eine richtige Reihenfolge zu bringen. Das ist aber alles außen vor. Es geht erst mal um die Ideen, die wir haben. Hier würde mich jetzt interessieren: Glaubst du, dass es angebracht ist, das so beizubringen, ist es zu abstrakt? Ist es für PhD-Studenten vielleicht nicht wirklich zielführend?

P: Unterschiedlich, glaube ich. mit dem Artbot zum Beispiel finde ich ziemlich cool, dass man quasi die Bilder so hinzieht und dann sieht, okay, man kriegt dieses Gefühl von der Wahrscheinlichkeit. Weil es wird nicht komplett rechts oder komplett links sein, sondern es wird irgendwo so in der Mitte landen. Das erste Bild, was du gezeigt hast mit diesen Begriffen im Gehirn, wo man quasi so ohne Hintergrund sieht und die so ablaufen muss, könnte ich mir ein bisschen zu verspielt vorstellen. Ich glaube, da tue ich, würde ich mich mit ein bisschen schwer tun und so denken, okay, was ist das jetzt Dein Algorithmus in die richtige Reihenfolge zu bringen, das finde ich wieder eine gute Idee.

Aber ich glaube, an manchen Stellen ist es vielleicht, wenn das quasi rumlaufen und die Sachen aus sich raussuchen, keinen zusätzlichen Lerneffekt hat, sondern einfach nur ein verspielter Teil von dem Ganzen, ist dann weiß ich nicht, wie sehr mir persönlich das gefallen würde. Weil wenn ich was sehe und das wirklich was bringt, und ich kann es in Zusammenhang bringen, dann habe ich ja Verständnis und das Visuelle irgendwie. Aber so rum ist Vielleicht ein bisschen schwieriger, aber es ist natürlich auch aus einem einzelnen Bild alles zu bewerten ein bisschen schwierig.

I: Das soll auch “nur ” eine Diskussionsgrundlage sein. Das ist der Ziel von der ganzen Arbeit, das mal was vorzustellen. Ganz kurz auch noch, weil das passt vielleicht auch ganz gut, die Idee ist dann auch, dass du noch nicht ausgearbeitet ist deswegen hier. Das ist so eine Art Bücherei, in der dann alles, was du gelernt hast, eingeordnet wird, eingesammelt wird, nochmal in eine richtige Skriptform mit links zu zusätzlichen Materialien, mit welches Spielewander zu angedacht, was für ein Lernziel sollte mit der Einheit erreicht werden, dass du hier nochmal so einen Überblick hast über alles, zum Nachlesen und aber auch zum nochmal selbst in einem Cheatsheet erstellen und vielleicht auch mal selbst was zum zusammenfassen.

P: Ich fände es ganz wichtig, ich finde es gut durchsuchtbar ist. Also die Idee finde ich cool, aber dass man quasi sagen kann, okay, wenn ich jetzt was über die Activation Function, wenn ich wieder was darüber da muss, dass ich nicht dann in eine neue Netzwerkstruktur gehen muss und dann finde ich quasi das, dann führt er mich da automatisch hin. Das ist weniger Spiel, das ist dann mehr durchsuchen.

I: Ja, aber das ist ja auch okay, das ist einfach eine Art von Ansicht, die dann nochmal für dich persönlich ist, um das, was du gelernt hast, in die echte Welt zu nehmen.

P: Und dass man vielleicht wieder dahin zurückgehen kann, wo man das Ganze gelernt hat, also nicht nur hier diese Bibliothek hat, sondern auch einen Link zu dem Level. Das sind zwei spontane Ideen Ja aber, das man so auf einen Blick nocmal sieht, was es gibt das ist so eine Inventory quasi.

I: Wie gesagt, da würde es mich jetzt tatsächlich noch interessieren, wenn du sagst, es ist zu spielerisch für dich jetzt,

P: Ja an manchen Teilen,

I: Ist dann der Gedanke ein komplettes Spiel zu haben, der Punkt, was an der Stelle wahrscheinlich problematisch wird und das ein normaler Online Kurs wie brilliant der Stelle dann angebrachter ist? oder wäre halt das Spiel für dich dann so was zu sagen, ich habe ein Spiel, ich habe keine Ahnung, von der Rundalnetz und ich mach das jetzt einfach mal, weil es ja nicht so schwierig und danach gucke ich mal weiter, also dass einfach die Einstiegshürde ein bisschen tiefer geht.

P:Das ist eine gute Frage. Also ich mochte Brilliant, ich mag das adaptive Lernen. Ich finde die Idee hinter allgemein super, dass man sagt, okay man passt sich quasi an das Niveau von denjenigen an, nicht dass der, der lernt sich, an die Vorlesung anpassen müssen, sondern dass die Vorlesung an sich an die Lernenden anpassen, finde ich ganz gut. Ob so ein Spiel das die Einstiegshürde für mich senken würde, weiß ich nicht, weil ich mach's ja in erster Linie - nicht um zu spielen, sondern um was zu lernen. Gerade wenn es mein PhD-Topic ist

I: Du hast einfach eine andere Motivation dahinter, das Thema anzugehen.

P: Ja, genau. Und es ist, glaube ich, für mich vielleicht ein schwieriges Mittelding, wo ich sagen wollte zwischen, okay, ist es als Spiel was, was ich quasi machen kann, damit es mir wirklich Spaß macht. Spaß ist ein schwieriger Begriff, weil das Lernen macht auch Spaß. Ich nenn's mal Spielspaß und Lernspaß wo man neue Sachen lernt, ist ja auch immer was Schönes. Aber ob ich ein Spielspaß habe, dabei das zu lernen, oder ob ich quasi neugierig bin, wissen will, wie es funktioniert. Und das so zu trennen... Schwierig. Manche Sachen, also sowas finde ich ziemlich cool. Ich finde Sachen, wo man dann sieht, okay, ich bastel irgendwas, wenn man die weights irgendwie einstellt und dann sieht, okay, wie verhält sich irgendwas Ich glaube, da gibt es viele Möglichkeiten, dass man quasi so spielerische Aspekte einbauen kann. Aber 100% spielen ohne quasi zu sagen, hier ist quasi ne Theorie-Seite oder sowas in der Richtung, ist vielleicht, finde ich, ein bisschen schwierig.

Deswegen tue ich mich wahrscheinlich auch gerade bei dem Collect-Terms schwer, weil das wäre was, wo ich sagen würde, okay, das sind einfach Folien, wo ich durchgehe. Und dann hätte ich zwischendrin dieses Spiel mit dem Begriffe einsammeln um das zusammenzubringen. Aber ich kenne es halt auch nicht, und das ist auch schwierig, weil wenn man es noch nie gesehen hat und ich weiß nicht so überlegen muss, okay, wie könnte das Ganze ablaufen ungefähr? Das kann viel cooler sein, als ich es mir vorstelle.

I: Ja, also, wie gesagt, man sieht ja auch so ein großer Punkt, ist es wirklich angebracht für PhD-Studenten, Erwachsene spielen auch gerne, aber ob es jetzt halt in so nem Kontext gerne spielen, um die anderen zu fahren?

P: Also, ich glaube zu Teilen ja. Also, gerade jetzt dadurch, dass ich aus dem Anwendungsbereich komme zu sagen, okay, ich habe was, wo ich mich spielerisch ranarbeiten kann und sage, okay, ich gucke jetzt nach, wie funktioniert das, wie funktioniert das, oder ich habe irgendwas gemacht. Und am Ende sehe ich dann, okay, warum hat das jetzt funktioniert, und habe dann die Erklärung dafür zum Beispiel. das finde ich cool. Oder zu sehen, ich habe irgendwelche Verbindungen oder so was, oder wie die Aufleuchten zum Beispiel, als ich mal ganz cool finde, wenn man irgendwie ein Auto fahren sieht und das hat irgendwie zwei, drei Sensoren und dann sieht man im neuronalen Netzwerk, wie diese Linien aufblinken oder so was in der Richtung. Vielleicht kann man daraus irgendwas machen. Also, es gibt da schon Teile, die ich cool finde und ich glaube, da ist spielerisch auf jeden Fall angebracht. Aber es ist halt auch ein Thema, was halt schon viele mathematische Grundlagen braucht für das Ganze und ich finde, es für fundamentales Verständnis und wie wird das optimiert und so [34:58.000 —> 35:00.000] und ob man das alles in spielerischem Content ohne die Theoriefolien quasi dazu packen kann - Das ist vielleicht ein bisschen schwierig.Vor allem, man muss das ja als PhD nachher sowieso lernen. Es bringt ja nichts zu sagen, okay, ich habe Bilder nach links und rechts gezogen und das Netzwerk konnte das dann.

I: Man muss es halt begründen können.

P: Man muss es halt begründen können, ja. Deswegen intuitiv, würde ich sagen, ich würde den an manchen Stellen den Spielerisch-Anspekt, da wo es sinnvoll ist, beibehalten und an anderen Stellen vielleicht fast schon so weiter wirklich zurückfahren. Aber vielleicht funktioniert es auch besser, als ich es mir vorstelle.

I: Ich hätte noch eine Frage, bevor wir das Gespräch beenden. Und zwar, noch mal zurück zu den Kompetenzen. Hast du dir noch einen Kopf, willst du das Mural noch mal kurz haben?

P: Ja, du kannst es mit gerne nochmal zeigen

I: Decken die Spiele das Ab, was wir versuchen in den Kompetenzen zu vermitteln.

P: So viele Spiele habe ich dafür glaube ich nicht gesehen.

I: So vom Prinzip her: also ich habe zum Beispiel dieses Datenlabeling, in dem es darum geht einen Bewusstsein zu schaffen, wie labele ich Daten, was kann man falsch dafür machen. Dann halt dieses Durchlaufen, um das Neuronalnetz kennenzulernen und die Brücken bauen, um mal zu gucken, wie sich das verhält. Gradient Descent und so wäre halt gerade diese Algorithmus und die Funktion, die man abläuft. Und dann mit dem kleinen Projekt am Ende, das nochmal alles zusammenbringt

P:Doch, ich glaube es hat es in großen Teilen abgedeckt.

I: Also wenn die Zielgruppe eine jüngere wäre, dann wäre das auch, wenn man jetzt mal von ihren Ph.D. Bedenken absieht, die man halt hat.

P: Ich sehe es vielleicht eher so fast schon Richtung zwischen Abi und Studium.

I: Aber noch nicht Also dann untere Stufen im Gymnasium?, P: kommt, kommt auf die Schüler an. Manche sind da voll motiviert für mich. Vielleicht habe ich schon ein Verständnis davon. Ich meine, wenn man eine Ableitung hat und weiß, hey, mit einer Ableitung mein Handy kann Bilderkennung machen, weil ich gerade in der 7. Klasse lerne wie ich ein funktion ableite . Das ist schon cool.

I: Also Verknüpft mit dem Thema, mit dem man die Grundlagen lernt.

P: Weil vieles da ja doch sehr abstrakt ist. Ob es funktioniert schon, weil es ja doch ein komplexes Thema ist, keine Ahnung. Ich glaube, ich habe alles durch. Gut, dann wirst du es von meiner Seite aus. Ich habe so viele Desktops, wo ich immer mich. . . Wenn du noch was loswerden willst, ist jetzt deine Chance. Ich bin gespannt. Das ist nur das Projekt vorzustellen. Das fertige Spiel ist dann wahrscheinlich eher. . . Das ist ganz weit in der Zukunft, denke ich. Was ich super spannend finde, das hatte ich auch vorhin schon wieder, so Adaptives Lernen. Wenn man die Level quasi alles wissen Man hat ja immer irgendwie Spiegel oder Quizze oder so was. Wenn man die Level quasi dran anpassen könnte, wie gut sich die Person quasi schlägt. Das finde ich super spannend.

A.6 Interview C: Beginner—Medical Technology

I: Dann hole ich dich erstmal mal mit dem Thema ab. Für meine Masterarbeit entwickle ich ein didaktisches Konzept. Es geht um neuronale Netze, also wie bringe ich neuronale Netzen jemanden bei? Unsere Zielgruppe sind PhD-Studenten, die die Thematik für ihre Arbeit brauchen, aber noch kein oder wenig Vorwissen haben. Ziel von meiner Arbeit ist dann nachher zu sagen, okay, wir haben eine relativ heterogene Gruppe auf einen gemeinsamen Nenner gebracht. Diese BGruppe hat ein bestimmtes Wissen, von dem aus sie sich in eine Richtung spezialisieren können und Paper dazu lesen können. Also, ich habe Wissen mit an die Hand bekommen, mit dem ich jetzt etwas anfangen kann in der Welt der Wissenschaft.

P: Okay, also Orientierung im Prinzip?

I: Ja, Orientierung oder auch schon mal den Begriff gesehen haben, mal gehört haben und schon mal so ein bisschen mit dem Thema warmwerden. Für das Lernkonzept haben wir uns ein Spiel überlegt Das unterscheidet sich von so Gamification insoweit, dass du nur einzelne Aspekte durch ein Spiel unterstreichst, sondern es ist alles ein Spiel. Also ein Lernspiel, mit dem ein Thema beigebracht wird. Das heißt dann Game-Based-Learning. Kennst du Mathe-Land?

P: Nee, aber wir hatten ein englisches Spiel. Und dann hatten wir den Mathe-Tiger

I: Ob sich sowas für NN wissen wir noch nicht. Das ist jetzt keine vollendete Tatsache, vor die du gestellt wirst. In so einem Lernkonzept gibt es Kompetenzen, die man vermitteln möchte. Und Design-Prinzipien ist für unseren Fall, also was für ein Rahmen vermittelt ich Kompetenze , wie sieht das denn aus. Und da, bevor ich dir das erkläre, nochmal kurz tu dir. Hast du schon mit neuronalen Netzen gearbeitet?

P: Ja, ein kleines bisschen im Bachelor.

I: Was war so die Thematik?

P: Ich habe mich mit Active Learning beschäftigt. Ich habe mich aber damals selber einarbeiten müssen, das war in der Corona-Phase. Das heißt, nur zu einem begrenzten Maß. Ich habe versucht mich über Grundlagen einzulesen. Mein Problem war, dass man aber einen großen Teil an Daten hat, die nicht gelabelt sind. Das kommot oft vor, z.B. in Medizin, weil labeln aufwendig ist, und Doktoren oft teuer sind. Und die Idee ist, dass du die Daten aaus den ungelabelten auswählst, von denen du dir erhoffst, möglichst viel Informationen zu bekommen, wenn sie gelabelt werden. Du hast sozusagen ein Netz, das zu einem gewissen grad trainiert ist. Und dann kannst du diese ungelabelten Daten irgendwie durchschicken und kannst dir dann anschauen, wie das Netz die Daten Labelt und wie unsicher es sich das ist. Ich muss ehrlich zugeben, ich weiß es gar nicht mehr so genau, wie genau das funktioniert hat.

I: Und dein Studiengang war Medizin-Technik.

P: Genau, Medizin-Techink.

I: ´In dem Interview gehen wir mehr auf die Design-Prinzipien ein und nicht so sehr auf die Kompetenzen. Ich werde dir trotzdem eine kleine Vorstellung in die Kompetenzen geben, dann in die Design-Prinzipien einsteigen und dir nochmal kurz Zeit geben, dir die Design Prinzipien anzuschauen.

Interviewer explains design principles P: [11:02.000 —> 11:07.000] Also nur vielleicht kurz nochmal als Zwischenfrage: Du möchtest nachher Feedback von mir zu den design Prinzipien bekommen?

I: [11:07.000 —> 11:18.000] genau. Was fehlt dir? Wie würdest du eine Umsetzung bewerten? .

Interviewer continues explanation I: [15:26.000 —> 15:31.000] Ich hoffe du hast einen Überblick bekommen und dann gehen wir jetzt die Prinzipien von vorne durch, damit du gezielt feedback geben kannst.

Ich zeige dir auch, wie wirt uns die Implemntation vorgestellt haben. Vielleicht fangen wir an mit dem Block Transparenz. Da geht es nämlich u die Struktur Und zwar, erstmal so um das große Ganze zu haben, haben wir den Hamster. Und der Hamster, der ist erstmal bewusstlos und muss erstmal seinGedächtnis/Gehirn reparieren Hier siehst du den Hamster und seine drei Welten: Am Anfang ist er in seinem Gehirn. Er muss sich da erstmal die Begriffe kennenlernen, das verknüpfen. Er geht dann weiter in doe nächste Welt, muss dann Überlebensfähigkeiten lernen. Also was ist Essen, ist kein Essen. Und dann im letzten Schritt kriegt er dann ein Überlebenszenario. Das ist diese grobe Struktur, diese Story, die dem Hamster folgt.

P: Also es ist sozusagen eine Story, die diesen Lernprozess begleitet. Und ich versuche sozusagen, das Gehirn von dem Hamster zu bauen.

I: Also genau, du willst ihn alles lernen lassen, dass er überlebt. Der Hamster muss am Ende überleben. Das mit dem Gehirnbauen wäre zum Beispiel dann ein Subziel, was du hast. Du musst halt erstmal wieder reparieren, dass es wieder funktioniert. Und dann hast du halt alles vergessen und dann musst du halt lernen. Und mit der Umwelt interagieren.

Dann für die andere Ebene der Struktur, für die Übersicht oder den thematischen Kontext, haben wir hier praktisch so eine Wissensbibilothek, Wenn du durch ein Level durchgegangen bist, wird das, was du gelernt hast, hier mit eingeordnet. ein Skript zu deinem Gelernten hast.

P: Das ist richtig gut.

I: Und die Idee ist halt auch, also du hast dann hier z.B. Level 1.1 gemacht. Und wenn du dann das Buch dazu aufmachst, dann kriegst du halt eine Übersicht mit: Was habe ich gelernt? Also ein Skript zu dem Thema. Aber auch zusätzliche Links, wo es weiterführende Ressourcen gibt. Es wird auch verlinkt mit was für einem Level du das gespielt hast. Also, dass du noch mal sagen kannst, ich mag da noch mal rein, Dass auch klar wird, was das Lernziel war von dem Level, was du gemacht hast.

P: [18:44.000 —> 18:46.000] Das sind dann wirklich generelle Informationen. Das oist dann kein Spiel mehr.

I: Genau. Das ist jetzt einfach wirklich wie ein Nachschlagewerk, mit dem Link zum Level dann halt.

P: Also im Prinzip, das Was ich vorher spielerisch gemacht habe, ausgeschrieben und untereinander wahrscheinlich auch verlinkt.

I: Genau, verlinkt und halt in eine Struktur gebracht, dass der Aufbau von dem Thema klar wird. Die Idee war auch, dass man dann so eine Art Notebook hat, wo man sich selbst noch mal einen Cheat-Sheet erstellt. Z.B. in Form von der Mind-Map, wo einfach nur die Themen angeordnet sind, und man sich noch mal Notizen dazu machen kann. Das ist die Struktur-Ebene, die wir auf der Informations-Seite haben. Dass du immer weißt, wo du dich im Thema befindest befindest, und auch den Überblick bekommst: Das habe ich schon gelernt, das kommt alles noch. Der Hamster ist der Agent, der dich da dann durchführt. Dann nimm dir nochmal Zeit zum Durchschauen und dann reden wirdirekt über den Block Transparenz.

P: Ist mit Structure hauptsächlich der Lernfortschirtt gemeint oder die thematische Structure?

I: Ja, ein bisschen was von beiden aber hauptsächlich die thematische Struktur. Das hängt aber zusammen: wenn du im Thema fortgeschritten bist, dann bist du auch in deinem Landprozess fortgeschritten.

P: Ich habe mich gerade gefragt, aber es kann ich weiterführende Themen irgendwie auch schon reinlesen, bevor ich die Spiele gemacht habe? Wird das irgendwie freigeschalten?

I: Meine Idee war das, freizuschalten

P: Und wie bekomme ich mit, dass ich was freigeschalten habe? Fange ich an, dieses Spiel zu spielen und dann mache ich immer weiter, und habe dann die Bibilothek im Hintergrund. Lese ich mir automatisch dann auch die Themen immer durch, oder ist eher so ein Nachschlagwerk?

I: Es ist als Nachschlagewerk gedacht. Die Idee war, dass du dann einen mehr dimensionalen Landfortschritt hast. Also nicht nur ich bin in der Welt fortgeschritten, sondern ich muss mich jetzt zum Beispiel auf die Anwendungen fokussieren. Und dann gibt es halt bestimmte Level, die halt anwendungsspezifisches Wissen beibringen. Und dass in der Bibilothek dann dieser spezifische Lernfortschritt gezeigt wird, z.B in Form von achievements.

P: Es ist eine andere Ebene, wo die Struktur nochmal thematisch verknüpft ist?

I: Genau, du kannst eine neue Ansicht öffnen in dem du in der Hauptansicht den Berg anklickst. Würdest du es anders machen?

P: Nein, ich finde das tatsächlich sehr gut. Weil das finde ich immer das Problem bei solchen Spielsachen. Es ist cool, dass du auch interaktiv bist dabei bist. Aber oft fehlt mir das, dass du dann trotzdem das nochmal nachlesen kannst. Und deswegen finde ich das eigentlich ein echt sehr gutes Konzept. Oft, wenn du so Spiele machst, dann denkst du das schon, das Richtige, aber manchmal halt auch nicht. Und es ist gut, dann nochmal definiert zu haben: okay, das ist wirklich die Lösung, das ist die Idee, die wir rüber bringen wollten. Oder auch, dass ich mich verlassen kann: Das was ich mir dabei gedacht habe, ist richtig Weißt du, was ich meine?

I: Ja wie eine Bestätigung.

P: Genau, wie eine Bestätigung. Das finde ich gut. Und deswegen auch die Frage, ob mir das automatisch angezeigt wird. Also z.B. da kommt irgendwie ein Achievement, und du kannst dir das Thema jetzt in der Bücherei das anschauen.

I: Also ich hatte mir so in Sinne von Collectibles auch irgendwie gedacht, dass du halt dann am Ende ein Thema für die Bücherei bekommst.

P: Und auch die Vernetzung zu, zu anderen Ressourcen außerhalb davon, das ist, glaube ich, auch sehr hilfreich.

I: Die Idee war auch, dass man vielleicht sich hier noch eine To-do-Liste oder so anlegen kann. Aber das kann man ja dann beliebig ausbauen

P: Da fällt mir auch nicht mehr groß ws zu ein.

I: Dann machen wir mal mir dem nächsten Block Different Peopke weiter. Da zählt natürlich einmal der Landprozess mit rein. Also, dass personen halt unterschiedlich viel Zeit brauchten Da war die Bibilothek natürlich auch angedacht als Mechanismus. Du kannst da hingehen und 20 Stunden durchlesen oder 20 Stunden YouTube-Videos angucken oder halt auch nicht. Also diese Zeitliche komponente - indivduelles Beschleunigen oder Entschleunigen. Weil es wirklichverschieden ist, wie schnell Menschen lernen. Dann abr auch die Thematik, dass Menschen unterschiedliche Lernstile haben. Manche brauchen mehr das Interaktive, dass ist dann klar inden Spielen abgedeckt. Aber dass wenn du Schreiben willst zum lernen, hier in der Bücherei dein Cheat-Sheet hast. Oder wenn du ein YouTube-Video angucken möchtest, hier dann einen Link findest. Also dass die Bücherei auch die zentrale Anlaufstelle ist, wenn du das anders btauchst, als es dir im Spiel aufbereitet und präsentiert wurde. Und gibt es noch die Komponente, dass verschiedene Menschen verschiedene Lernstände, verschiedene Ziele haben. Dazu hatten wir uns überlegt, dass man verschiedene Modi zum Beispiel einführt. Z.b. einen Mathe-Modus hat oder einen Programmier-Modus, Und dann nach Bedarf ein oder ausschalten kannst. Oder wenn es sich zusätzlich interessiert bzw. du fortgeschrittenes Wissen über ein Thema benötigst. hier über de Hilfe-Button auf die zusätzlichen Ressourcen, die auch in der Bibilothek sind, kommst. Oder wenn du stecken bleibs und Hilfe brauchst, dass es hier dann Tips oder nochmal eine ander Erklärung zu dem Thema gibt. Die Idee ist, dass wenn du zusätzliche Informationen brauchst, direkt in einem Level die Infos bekommst und nicht in Bibilotheksansicht wechseln musst.

P: Also eine Sache, die ich mal nachfragen wollte ist: du hast ja gar von der Geschwindigkeit geredet. Es gibt da zwei Seiten, was die Geschwindigkeit angeht. Das eine ist, wie schnell komme ich während der Zeit, die ich reinstecke voran. Und die andere ist, wie viel Zeit am Stück kann ich reinstecken.

I: [27:27.000 —> 27:29.000] Also ich jetzt habe davon geredet, wie lange man braucht um ein Thema zu verstehen.

P: Okay, also wie wie viel, wie schnell kann ich dem Spieler neue Sachen zumuten?

I: [27:45.000 —> 27:47.000] Genau.

P: Also worauf ich hinauswollte ist, vielleicht kommt es auch darauf an, dass verschiedene Leute verschiedene viele Zeit zum investieren haben. Also es gibt vielleicht Leute, die wollen das abends mal für eine viertel Stunde machen. Und die einen anderen, die setzen sich dann zwei Stunden am Stück ran, weil sie sich schnell in das Thema einarbeiten wollen Also z.B. Du fängst gerade deine Masterarbeit an. Dann machst du das vielleicht auch mal ein paar Stunden am Stück - also schnell viel Info auf einmal. Wenn du dich jetzt aber neben dein Beruf da irgendwie einlesen willst, damit du das irgendwann mal machen kannst, dann machst du das vielleicht eher eine Viertelstunde mal am Abend. Das sollte man noch beachten.

Die zweite Sache, die mir noch eingefallen ist und das mir oft als Nicht-Informatiker aufgefallen ist, der sich mit Informatik beschäftigt. Die Sprache, die von Informatikern verwendet wird, ist nicht leicht verständlich. Was vielleicht auch daran liegt, dass in Foren oft abgekürzt und vereinfacht wirdirekt. Das wird wahrscheinlich bei euch nicht so sein,a ber ihr solltet dran denken, [29:09.000 —> dass ihr auf Sprache achten sollte. Und dass es auch verschieden Modi vielleicht auch für Informatiker und für nicht Informatiker gibt.Oder dass es verschiedene Beschreibungen gibt, um da einen Unterschied zu machen Das war die zwei Sachen, die mir eingefallen sind.

I: Oh ich habe hier vergessen einen Punkt, mit dir zu besprechen. Da geht es auch so in Richtung Challenge und Interaktion. Du hattest ja mal Duolingo verwendet. Die haben ja auch diese täglichen Challenges als Mechanismus, um gezielt auch Themen zu wiederholen kannst. Die Idee ist, dass es in unnserem Konzept Mini-Games oder Mini-Challenges pro Thema hast. Die kannst du beliebig oft wiederholen, wenn du sagst, das würde ich jetzt aber gerne nochmal üben und mit denen du deinen Lernstand überprüfen kannst. Aber halt in der Art und Weise, dass es halt dann doch nicht immer ganz das Gleiche ist.

P: Du meinst, dass man wie bei Duolingo das gleiche Level sozusagen, immer wieder machen kannst und dann wird es irgendwie schwieriger, weil sie weniger Hilfestellungen geben.

I: Genau. Oder mit unterschiedlichen Wörtern. Weil das in dem Haupt-Spiel selbst zu variieren, ist wahrscheinlich schwierig. Die Kernidee ist also einen seperaten Übungs-Mode zuu haben.

P: Challenges sinf bestimmt auf jeden Fall wichtig. Oder ein ander Mechansimus: Lernen, Lernstopp, Lernen, Überprüfungen.

I: Die ursprüngliche Idee war auch, dass du praktisch zum Weiterkommen einen Quiz lösen musst.

P: Das ist eine gute Idee.

I: Das wäre dann halt auch so das Gleiche, was mit diesem Lernfortschritt eingeht, wenn du halt verschiedene Dimensionen von Lernfortschritt hast. Das dann auch, wie oft habe ich es schon geübt, mit in denLernfortschirtt mit rein geht. Also, dass z.B. eine sehr einfache Metrik hat: Du hast 100 Prozent, wenn du Level 1 bis 5 gemacht hast und dabei Level 2, 10 mal gelernt und Level 3, 5 mal gelernt hast. das sind dann halt die 100 Prozent, dass da so mehrere Faktoren noch einspielen.

P: Auch wenn es dort vielleicht gut wäre, wenn du dann irgendwie abstimmen kannst. Dass du halt je nach Skill, manche Themen vielleicht öfters wiederholen kannst, als andere Also, dass das nicht so vorgeschrieben ist was du wiederholen musst. Bei Duolingo ist es ja so, dass du eine gewisse Anzahl Kronen irgendwie sammeln musst. Und Kronen bekomsmt du, wenn du ein LEvel gemacht hast. Und dann kannst du das Level wiederholen, dass dich irgendwie mehr interessiert, oder das wo du denkst, okay, da brauche ich mehr. Dass man das irgendwie vielleicht individuell machen kann.

I: Man kann sich auch überlegen, dass man halt so wie so ein Skillbaum macht, dass du dann halt irgendwie den Anwendungshamster hast und der hat halt andere Herausforderungenals in der Mathehamster.

P: Ja, genau.

I: Wenn das für dich passt, machen wir mal mit dem nöchsten Design Prinzip: Reachable Success weiter. Da geht es um die Visualisierung von so einem Lernfortschritt. Bei uns ist halt einmal durch das Level durchgehen, also die Level anzeige.

P: Das sind wie bei Mario

I: Ja, genau. Dass ist dann diese Übersichtskarte über die Welt. und dass es zusätzlich einen Fortschirttsindikator innerhaln der Levels gibt, der dir anzeig, wie viel dir zum Abschließen des Levels noch fehlt. Man kann das auch verdeckt machen also z.B. hier siehst du die letzt Insel hat er noch nicht erreicht, deswegen ist sie noch versteckt hinter den Wolken. Dann brauchen wir auch eine Hilfe button, über den wir schon geredet haben. Der verhindert, dass du irgendwo stecken bleibst und nicht weiter kommst und der dir dann auch Tipps gibt, also Tipps und Hilfe, die dir dann beim Lösen des Levels helfen. Der kann dan auch noch die verlinkung zurweiteren Ressourcen haben, wenn du halt dann nur aus Interesse liest. Und dann eine Art von Kollektible, die in dem Spiel auf eine sinnvolle Art verwendet oder ausgegeben werden kann. Wir haben jetzt hier Coins gemacht. Da stand dann auch die Idee im Raum, dass man genug Coins haben muss um ein Neues Level freizuschalten.

P: Das geht dann auch so in richtung Duolingo. Da brauchst du auch genügend Kronen um ein neues Topic freizuschalten. Und du auch eine Challenge überwinden. Da wird dann dein Wissen nochmal getestet wird, innerhalb von der Insel in deinem Fall.

I: Man kann sich auch überlegen, dass man halt irgendwie Futter sammelt und das mit NPCs tauschen muss, um überhaupt eine Aufgabe zu bekommen. Wichtig ist,d ass es für das Lösein einer Aufgabe eine Reward gibt. und der Reward einen Nutzen in dem Spiel hat. Gerade wenn du das Beispiel mit Duolingo gebracht hast, Eine Funktion, die die haben und die ich sehr motivierend finde oder viele Leute, glaube ich, sehr motivierend finden, ist Interaktion mit anderen Lernenden. Also, die haben dort zwei Sachen. Das eine ist, du kannst Freunde irgendwie mit dir connecten und dann siehst du immer, wie weit die sind, wie viele Punkte du hast, wie viele Punkte wir haben. Und es gibt Liegen, wo du kannst innerhalb der Woche Punkte sammeln kannst Und am Ende der Woche kriegen halt die Leute mit den meisten Punkten, kommen in die nächste Liga, die Leute mit den wenigsten steigen wieder ab. Und dadurch wirst du halt motiviert dabei zu bleiben. Das ist implentierungstechnisch bestimmt schwirig, ist aber eine Dimension, die über die ihr nachdenken könnt Also das Wettkämpfe, also weil es kompetitiv ist, immer sehr motivierend sind. Wie sieht es mit so Achievements aus? Z.b du bist der Mathekönig.

P: Ja, ich schätze auch. Ich glaube, da sind halt Leute auch verschieden. Ja, da kommen wir auch auch noch. Da kommt immer sehr drauf an, was dich motiviert. Achievemnts sind es eine Sache. Wenn du dir irgendwas aufbauen kannst, oder du kriegst einen neuen Skin, oder einen neuen Hut, eine neue farbe oder. Das hilft auch immer nicht direkter Spiel Nutzen aber persönlich Oder hat eine neue Farbe

I: Dann kommen wir zu dem Thema Komplexität, mit dem tue ich mich selbst auch noch schwer, das kannst du halt so spielelementechnisch nicht einfach umsetzen, weil es halt viel um den Inhalt geht. Also du musst dir klar sein, was ist das kleinste Atomare Teil, was ich jetzt ja, oder wie groß darf die Einheit jetzt sein, das sie nicht zu komplex ist. Und das ist natürlich die Frage, was heißt zu komplex, und das ist eine andere Diskussion. Das heißt, was wir uns halt jetzt hier überlegt haben, ist halt einfach dieses Aufpassen. Was habe ich beigebracht in dieser Unit? Und dann aufpassen, was bringe ich in der nächsten Unit bei und hängt das zusammen? Bzw. bei uns sind das dann die Level. Das hängt natürlich dann damit zusammen, dass ein Level,jetzt keine 20 Stunden gehen sollte, sondern halt z.B. maximal 10 Minuten.

P: Also eine möglichst eine kleine Einheit, die eine Information enthält.

I: Genau und dass man schnell Erfolgserlebnisse bekommt.

P: Ein wieter Punkt, ist das Thema von oben nach unten zu erklären. dass das das Ziel ist, dass du erstmal alles Komplexe wie eine Blackbox behandelst und erstaml grob erklärst. Also irgendein Input und irgendein Output un dann spiel mal.

I: Genau, und dann im nächsten schritt schauen wir mal, warum war das jetzt so, [38:19.000 —> 38:21.000] warum hat das jetzt so funktionert.

P: Aber ich glaube, dass wir den Units möglichst klein zu machen, ist auf jeden Fall gut. Dann hast du ja auch wieder dieses Klassische: Ich komme tatsächlich auch voran zum einen, und zum anderen, dass es nicht zu viel zu verarbeiten ist.

I: Und man setzt dich halt vielleicht auch mal schneller hin. So nach dem Motto: heute mache ich mal 2 Inits.

P: Also gerade auch wenn, was ich vorgesagt habe, wenn du sagst, es gibt Leute, die wollen das stundenlang ein Stück machen. Aber es gibt halt auch Leute, die wollen das nur mal schnell machen. Und dann ist es halt gut, das graduell zu haben, modular. Und das war vielleicht auch ein Ding, damit du halt die Sachen irgendwie wiedererkennst. Also, du lernst am Anfang die Blackbox kennen und danach gehst du halt reinund schaust dir einzelne Elemente irgendwie an. das ist sozusagen die Blackbox, zum Beispiel, auf eine Weise darstellt es bildlich und dann diese gleiche Darstellung halt immer wieder verwendest.

I: So eine konsistente Visualisierung.

P: Konsistente Visualisierung, genau. Genauso, wenn ich immer eine Layer habe und dann stelle ich die Layer auf eine bestimmte Weise da. Und da drin sind dann wieder Neuronen und dann stelle ich die Neuronen wieder auf eine gewisse, also weißt du, dass dusolche visuelle Elemente hast, die du wiedererkennst. Ich glaube, das wäre sehr hilfreich, damit du dann dort die Orientierung nicht verlierst. Und dann kannst du ja so langsam in diese komplexe Tiefe reingehen. Sagt sich natürlich leichter, als gemacht wahrscheinlich,

I: Dann sind wir jetzt auch bei diesen interaktiven Elementen, angekommen Wichtig ist, dass du irgendeine Art von Motivation am Anfang hast, mit der du du das Thema motivierst. Das könnte man mit halt einem animierten Intro machen, zum Beispiel. So wie es halt in Spielen oft ist, ja, mit so einer Eingangssequenz.

P: Also dass der Hamster erzählt,d ass er einen Unfall hatte

I: Genau und, dass man auch die NN Thematik motiviert Klar, dann diese Interaktion mit dem Content, mit Challenges oder halt Puzzles, Quizzes. Eine aus der Umfrage doch gemeint,sie findet so ein Escape Room-Konzept

P: auch super cool.

I:Also, dass man bekannte Visualisierungen mit einbaut. Und dass man sich vielleicht auch für mathematische Konzepte entsprechend was überlegt. Und hier, das geht jetzt auch in die Richtung von dem Praktisch-Feedback und Überprüfungsmechanismus, dass du halt Quizzes hast, die dem User Feedback geben. Und dir halt auch helfen, einzuschätzen, wo du stehst.

P: Ein Gedanke dazu vielleicht. Ich weiß nicht, welcher Anspruch ihr da habt oder welche Zielsetzung ihr im Kompletten habt. Also, ich frage deswegen, weil ich, wenn ich so nachdenke, wie Leute spielen, also ich selber spiel zu wenig so viel, aber ich kenne es trotzdem, dass es gibt Leute, die haben total Spaß daran, wenn sie irgendwie so eine Story haben und dann irgendwelche Side Quests und was auch immer. Und es gibt andere, die wollen eigentlich hauptsächlich einfach durch und schnell vorwärts kommen und dann stört es vielleicht ein bisschen auch, sich irgendwie Sequenzen zu zwischenzuhaben, und wo es dann den Lernprozess stört. Dass die dann irgendwie optional sind Oder dass man die skippen kann

I: Hättest du eine Idee, wie man so eine Motivation dann nicht optional macht? Weil in so einer Sequenz dann auch eine Sequenz vermittelt wird. Und dann musst du sicherstellen, dass die Kompetenz auch vermittelt wir, wenn der Player die Sequenz überspringt.

P: Ne, okay, das ist dann natürlich wichtig, das braucht's.

I: Ich verstehe natürlich auch den Punkt, dass man sagt, ich kann das überspringen, wenn mich das nervt. Aber hättest du eine Idee, wie man jemanden, der jetzt Skip gedrückt hat, trotzdem noch die Kompetenz mitgeben kann?

P: Also, die stumpfe Brute Force Methode, wäre alternativ einfach einen Text zu schreiben. Also, keine Ahnung. Da kommt der Hamster und er erklärt, was jetzt die Motivation ist. Und dann sag ich, Skip, und dann kommt halt stattdessen ein Schirm, wo drei Stichpunkte stehen. Wo dann steht: Du hast gerade geskippt, Folgende Informationen kamen gerade. Das wäre natürlich die einfachste Möglichkeit. Aber das wollte du ja eigentlich nicht machen. Ihr wolltet ja eigentlich spielerisch das Ganze machen.

I: Ja, weil ich meine, dann hast du dich in dem moment halt für Text entschieden..

P: Das wäre eine Option.

I: Oder würdest du sagen, du würdest halt thematisch überhaupt nichts in Animationen und Videos machen?

P: Ich glaub tatsächlich, das ist gut, wäre das zu trennen. Das ist eine Überlegung, dass du sagst, Spiele sind immer wirklich, ich vermittel grad im Moment eigentlich möglichst viel nur Verständnis und irgendwie Zuordnung und so. Und dieses ganze Drumrum, was jetzt die Belohnung angeht, was die Story angeht, was die Visualisierung mit dem Hamster angeht, dass das halt Drumherum ist,

I: Also so on top.

P: Genau. Und dass sobald ich irgendwie Zeit investiere und halt irgendwie grad aktiv was mach, das wirklich nur inhaltlich ist. Dann hab ich sozusagen eine möglichst hohe Zeitnutzung. Und wenn ich dann Spaß dran hab, dem Hamster zuzuschauen, wie er irgendwie da rumläuft, oder so, dann kann ich das ja immer noch machen. Also das du das irgendwie trennst.

I: Du hast gerade schon angesprochen mit den verschiedenen Spieletypen. Du hast auch gemeint, dass du zwar nicht spielst, aber ich würde dir trotzdem kurz bitten, dich einzuschätzen.

Interviewer explains player types P: [Also wenn ich jetzt an meine Erfahrung denke, dann bin ich auf jeden Fall achievermäßig. Dieses irgendwie weiterkommen und dann hast du irgendwie eine neue Farbe oder ein neues Level oder so was. Kompetition tatsächlich weniger auch wenn die zwei irgendwie verwand sind. Aber es ist glaube ich weniger dieses Beste sein als andere, sondern einfach halt das für mich selbst gut sein. Also Kompetition hilft schon auch, aber hauptsächlich eben dieses irgendwie Levelmäßig hochkommen. Und ansonsten socializing.

I: Du hast ja auch vorhin gemeint, dass es Freunde-Bord gibt und das Nicht-Freunde- Ranking. Ist dir da das Nicht-Freunde-Ranking wichtiger?

P: Das ist eine gute Frage. Bei Duolingo hat mich tatsächlich mehr diese Liga motiviert. Das wäre eher dieses Kompetition als Freunde. Aber es liegt vielleicht auch darin, dass ich halt einfach nicht so viele Freunde hatte, dort connected in Duolingo speziell. Ich glaube die einzige Person, die connected war, war meine Schwester und die hat das nicht so aktiv mitgemacht. Also da liegt es dann halt einfach an aktiven Personen, herausfordern herausfordern, Es muss nicht zwangsläufig dein Freund sein, Unabhängig vom Spiel: Zum Beispiel im Sport hilft, es mir immer sehr, wenn andere Leute mit mir Sport machen, weil du dich dann irgendwie halt dich nichtdrum drücken kannst.

I: Ja die Motivieren dich dann Extern. Also bist du so Achiever mit Fokus auf etwas Kompetition?

P: Ja genau, ein bisschen Kompetition. Und da gehört natürlich Socializing dazu. Aber ich muss jetzt nicht jedes Side-Quest gemacht haben, also ehern nicht Explorer.

I:Dann würde ich jetzt noch kurz über die Spielkonzepte gucken. Da würde ich dich bitten darauf zu achten, Ob dir so ein Spiel Spaß machen würde. Und ob dich das Spiel motiviern würde

Interviewer presents game concepts P: [Zu dem Sammel Spiel] Arbeitet ihr auf der Kompetenzebene dort mit Analogien zur biologie? Oder geht es wirklich rein technisch?

I: Ich habe mich jetzt zu entschieden, ein bisschen impliziter zu machen, indem man sagt, man hat jetzt ein biologisches Gehirn, in dem man sich bewegt, aber die Begriffe werden dann technisch erklärt.

P: Okay, ja, jetzt macht es wahrscheinlich Sinn. Das ist eben was, was man glaub ich aufpassen muss, dass man ein Ziel ist, das jetzt zu lernen. Und gerade wenn der Zielgruppe jetzt nicht Grundschulkinder sind, sondern PhD-Leute, dass du dann auch schon Spaß hast dabei, aber halt den Lernteil nicht vernachlässigst [53:21.000 —> 53:23.000] Lieber wir fokuss darauf hast und nicht die Spiele überdimensionierst. Ich glaube, das ist glaube ich oft ein bisschen so eine Schwierigkeit bei dem Thema.

I: Würde, rein vom spielerischen her, so ein Mechanismus (durch die Welt laufen und dinge sammeln) dir das Spaß machen?

P: Doch schon, kann ich mich nicht vorstellen. Also, es ist natürlich schwierig vorzustellen, weil das ist erstmal noch ein sehr grobes Konzept so, aber grundsätzlich. Oder es wäre besser da irgendwie ein anderes Lernziel zu haben, als das Begriff zu erkennen?

P: Geht es um einen bestimmten Teil jetzt, zum Beispiel das Neuron, oder geht es wirklich um allgemeine Begriffe von überall her?

I:Das kannst du dann beliebig definieren für deinen Anwendungsfall.

P: Da ist es wichit, dass man immer schauen sollte,dass die Zuordnung passt und dass ich jetzt auch nicht den Überblick verlieren. wenn ich ganz allgemein Begriffe erkläre und die Begriffe sind es aber auf der Ebene von der Blackbox, oder teilweise von irgendwelchen Aktivierungsfunktionen, dass man da aufpasst, dass man da zu weit entfernt ist. Also, weil einfach irgendwelche Begriffe zu bekommen ist halt immer schwierig zu merken, wenn du keinen Kontext dazu hast, was mache ich da eigentlich?, Deswegen ist es, glaube ich, Es ist cool, wenn du das Neuron erklärt hättest oder okay, du erklärst, okay, jetzt will ich irgendwie was haben mit Inputs und Outputs. Und dann gehst du halt zu den einzelnen Bestandteilen von so einem Neuron. Also, das ist halt irgendwie nicht zu weit bestockt, bis es klappt.

I: Die Anwendungsebene, praktisch noch auf der rechten Seite, hast du links die Begriffe und rechts aber immer den Bezug zu,

P: Genau, irgendwie muss klar bleiben, was bedeuten diese Begriffe und in welchem Kontext stehen die und wieso heißen die so, wie sie heißen. Das wäre aber auch wichtig davor zu wissen, ne? Eigentlich schon, ja. Aber dass du irgendwie vorher weißt, da geht was rein, da geht was raus. Also, dass man ds vielleicht auch gar nicht, mit vielen Begriffen auf einemal macht, sondern halt erstmal einen, den dann erlebt und dann erst der nächste. vielleicht hast du irgendwie die Begriffwelt und du kannst halt immer nur die Begriffe lernen, zu denen du schon was gemacht hast. Z.B. werden Neuronen erklärt Und sobald du dort irgendwie weit genug bist, kannst du in die Begriffewelt irgendwie reingehen und dann lernst du die Begriffe. Oder andersrum: du gehst zuerst in die Begriffewelt dort. Also, ich weiß es nicht wie, aber das ist halt irgendwie. . . Du kannst es schon als eine Einheit lassen, aber halt, dass du dann diese Connections hast zu diesen anderen Themen.

I: **[Vorstellung Dark Cave]**

P: Ich finde das Prinzip super.. Du musst sozusagen die Stelle an der Schlucht, wo der Abstand zu kurz am kleinsten ist?

I: Genau.

P:in dem Fall wäre ich mir jetzt nicht so sicher, was ich überhaupt sehe. Dann wirst du vielleicht an der Visualisierung noch ein bisschen arbeiten. Aber die Idee in sich finde ich gut.

I: **[Vorstellung Save the Frog]**

P: Geht es hier jetzt um das gleiche Zile, also das Minima zu finden?

I: Hier schon, aber allgemein kannst du das unabhängig machen. Wichtig ist ,dass Kontext bekannt ist, in dem sich das Spiel befindet Hier ist es jetzt so, der Hamster ist über den Abgrund gekommen und der frosch muss noch drüber. Der Hamster muss ihm erklären, wie es geht oder ihm helfen eine Brücke zu bauen

P: Das ist gut. Dann ist es cool, wenn du ihm als erklären musst, wie du es gemacht hast, anstatt ihm eine Brücke zu bauen, Du sagst ihm halt: okay, so findest du die kurze Stelle, so gehst du vor und dann ist das zu sagen die Anleitung. Weil dann hast du diese Connection zu dem anderen Spiel. Der Algorithmus, ist das so pseudocode-mäßig gedacht?

I: Ja, also das ist also erstmal weit weg von eine richtigen implementuerung und einer Sprache Und dann kann dich der Frosch natürlich auch belohnen, er es geschafft hat.

P: Das finde ich cool. Nur vielleicht eben diese Kontext. Genau, weil dann hast du so eine bessere Connection zu dem, was du vorher gemacht hast. Wenn es so immer wechselt, da habe ich das gemacht, dann mache ich plötzlich was anderes, dann ist das sehr orientierungsschwierig.

I: Da muss man halt im Hinterkopf bereiten, dass die Einordnung in den Thmateischen aber auch spielerischen Kontext wichtig ist.

I: **[Vorstellung Build Bridges]**

P: Ich habe bloß grad gedacht, also ich weiß nicht, ob das dann das zu kompliziert macht, ob das vielleicht dort jetzt zeigen wollte, aber dass man irgendwie mehrere Neuronen hat. Also mehrere unterschiedliche Neuronen, die sich verscieden verhalten. Weil in dem Fall das ist ja sehr linear. Vielleicht kannst du auch mehrere Levels daraus machen, also du fängst linear an und machst dann noch mal komplizierter. Wie findest du das vom Erlebnis her, wenn du noch nichts von Gewichten weißt was ich ein bisschen vermisse ist das ausprobieren, weil es jetzt irgendwie sehr linear ist. Du heißt einfach nur, du gehst hoch und dann geht es halt auch hoch. Da weiß ich nicht ob klar ist, was eigentlich passiert. Das ist vielleicht die Überlegung gut, Neuronen mit unterschiedlichem Verhalten zu haben. Irgendwie musst du noch mehr rumspieleneren können, schätze ich. Ich meine, du könntest z.B. einen Slider haben um das mehr oder weniger zu aktivieren.

I: Was meine Gedanke war beim erstellen, das kommt es darauf an, wieder damit entdeckieren kann. War halt so ein bisschen einfach nur zu gucken, wie beeinflusst Gewicht. So, das ist den Output und dann wird es aktiviert mit den Gewichten, einfach so ein bisschen in der Visualisierung mit ein paar Spielereien, die man machen kann. Das ist so ein bisschen der Hauptgedanke von dem Ding. Aber ich finde auch so ein bisschen gleich dropmäßig, das ist natürlich auch noch cool.

P: Und vielleicht kannst du auch verschiedene Neuronen verwenden. Also es gibt Typ 1, Typ2 und er eine aktiviert halt früher und der andere ist später. Oder der eine gewichtet mehr, der andere nicht. Also damit du irgendwie noch einen Vergleich hast, vielleicht, oder eine Referenz oder irgendwas. Weil jetzt dort, also klar, ich habe einen Weight, der macht das höher. Aber wenn ich jetzt das Konzept von Weights nicht kenne, dann ist mir das ja im Moment relativ egal, ob der es von 5 auf 20 geht oder ob der die 5 einfach überträgt [Ich habe beide Male halt den Effekt erreicht, den ich will. Es fehlt vielleicht noch die Natur von der Neuron, dass man das irgendwie noch mal besser versteht. Also zum Beispiel, wenn du sagst, ich habe zwei verschiedene Neuronen, die ich beide einsetzen kann, das eine weightet mehr als das andere, das würde ja schon zeigen, manchmal aktivieren die mehr, manchmal weniger. Das würde schon reichen.

I: Also fast noch ein bisschen abstraker, dass man das mit dem Weight noch ein bisschen mehr versteckt?

P: Ja. Aber das kommt darauf an, welches Konzept du zeigen willst. Wenn du dir Activation zeigen möchtest, dann bräuchtest du welche, das eine feuert früher, das andere später. Wenn du dir Gewichte zeigen möchtest, dann würde das reichen einfach das eine feuert stärker, das andere weniger stark. Wenn du beides zeigen möchtest, dann kannst du vielleicht auch ein kleines Netz aufbauen. Du kannst ja auch nach und nach aufbauen. Also dann geht es ein paar Inseln weiter unnd dann musst du plötzlich anfangen, okay, das eine aktiviert früher, das andere später und dann kannst du noch mal anfangen mit das eine aktiviert negativ, das andere positiv. Also du verbinest mehrer typen. Und du kannst ja die Komplexität steigern. Aber ich glaube, es hilft, relativ simpel zu bleiben und abstrakt.

I: **[Vorstellung Artbot Good or Bad]]**

P: Suchst du hier nach Ideen?

I: Ich suche nach Feedback. Also z.B. was du gut findest von einem spielerischen aspekt aus

P: Wichtig ist glaube ich, dass die Message klar wird, wie ich das vorher mit dem Besipiel gezeigt habe. Also dass verschiedene neuronen verschieden stark sind. Oder hier, dass der Hamster falsch als Bär erkannt wir. genau, das Konzept finde ich sehr gut. Hätte ich auch, glaube ich, auhc Spaß daran.

I: Wenn du dir das Thmea NN für deine Arbeit nochmal aneignen müsstest, hättest du Interesse an so einem Spiel? Würde dich das jetzt motivieren mit den Konzepten, die ich dir gezeigt habe. Würde es dich motivieren? Ist es halt vielleicht dann doch zu kindlich? Muss man irgendwie da was anderes vom Konzept her anders machen oder von dem Spielmechanismen anders machen?

P: Das ist eine schwierige Frage. an sich finde ich das sehr cool. Und auch viele von den Sachen, fande ich gut, Das Gute ist, und gerade vor allem, wenn ich mir vorstelle, ich weiß echt noch nichts oder kaum was über NN, dann ist es schon auch hilfreich damit die Konzepte zu verstehen. Ich muss aber auch sagen, wenn ich jetzt dran denke, dass ich jetzt irgendwie unter Zeitdruck stehe und dann musst du halt aufpassen, dass das Also, gerade spielerisch ist cool, aber da müssen dann schon schnell genug die Fortschritte kommen und eigentlich musst du [01:13:39.000 —> 01:13:41.000] möglichst vie Konzept zeigen in möglichst kurzer Zeit und das ist das wo man [01:13:43.000 —> 01:13:45.000] bei dem Thema am meisten aufpassen muss.

I: Was waren für dich so die motivierendsten Elemente?

P: Wenn ich jetzt anfange viele bilder zu label, dann kommt die Message schon rüber, aber dumusst aufpassen dass das nicht zu viel wird.

I: Also, ein mechanismus kein konkretes spiel.

P: Ich überlege noch kurz. Also dieses Algorthmus schreiben ist immer gut.

I: Also du darfst ja auch gerne auf diese Lernelemente, diese Designprinzipien, die ich dir vorgestellt habe beziehen Weil im Prinzip habe ich jetzt gerade vorgestellt, wie wir halt vorhaben, diese Prinzipien umzusetzen in den Mechanismen.

P: Also eine Sache, die ich, wie gesagt, das habe ich vorhin schon erwähnt, sehr cool finde, ist diese Idee mit der Bibliothek die ich im Hintergrund noch habt. Gerade wenn ich auch eben die Anspruch habe, da auch wirklich für höhere Level den Inhalt beizubringen, oder Leute,, die direkt anwenden wollen, [01:15:59.000 —> 01:16:01.000] Dass du dann auch einen überblick hast, was du machst. Dann so visuelle Sachen. Das finde ich, glaube ich, sehr hilfreich.

Also wenn, dass jetzt die Welt ist, in der ich sehe, dann kommen, oder irgendwelche Connections oder irgendwelche Elemente, die ich wiederkenne, das, was ich vorhin gemeint habe, mit visuell wiederkennbar die Blackbox, was auch immer. Ich glaube, solche Sachen helfen, damit du das auch im Kopf behälst. Dann hast du jedes Mal, wenn du das ausprogrammierst, wieder die Blackbox vor Augen. Ansonsten, klar, solche Sachen, wie jetzt den Hamster als Feind Lablen, Also Prinzipien, die du irgendwie visuell darstellst oder auch mit der Schlucht - ich schau hier, ich schau da. Und dann ist halt, wie gesagt, wichtig, dass du halt schaust, dass du nicht zu lange brauchst für die Spiele oder zu kleine Spiele machst ist.

I: Wenn es gerade noch ein Gedanke kommt, dann würde ich kurz sagen, dass ich ihn aufgenommen habe, nicht, dass ich ihn vergesse. Und zwar würdest du sagen, für den PhD-Studenten wäre das fast besser, man sagt, man geht von dieser Bücherei aus, die man hat, und hat dann halt ähnlich diese Online-Kursstruktur nur halt von der Bücherei aus in einer Hamsterwelt anstatt zu sagen, ich bin ein Hamster, der durch die Welt läuft und sammele dann für die Bücherei. Du musst mir die Frage überhaupt nich beantworten. Ich verstehe, was du meinst, aber ich muss kurz überlegen. Das ist jetzt auch nur, wie gesagt, dass es drauf ist, du wirst es nicht vergessen.

P: Das ist eine sehr gute Frage. Ich glaube, das kommt ein bisschen darauf an, wie es spielt, wie es einzigt. Und das ist, glaube ich, sehr anspruchsvoll. Diese Message, das rüberzubringen und die gut aufeinander aufzubauen,dann finde ich die Welt vor der Bücherei besser. Damit du es verstehst, bevor du es in der Theorie nachliest, irgendwie. Zumindest intuitiv. Das stelle ich mir aber sehr schwierig vor und das könnte passieren, dass du dann den Überblick verlierst. Und dann würde das vielleicht helfen, erst die Bibliothek zu haben und dann wieder in die Welt.

I:Gut, ich glaube, das war's. Ich weiß nicht, fällt dir noch was ein, was du unbedingt loswerden möchtest?

P:Nicht spontan.

Declaration

I hereby declare that the work presented in this thesis is entirely my own and that I did not use any other sources and references than the listed ones. I have marked all direct or indirect statements from other sources contained therein as quotations. Neither this work nor significant parts of it were part of another examination procedure. I have not published this work in whole or in part before. The electronic copy is consistent with all submitted copies.

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