UTRECHT UNIVERSITY

THESIS

Eagle Eye: a progress measure for intelligent tutoring systems

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August, 2018

Abstract

The aim of intelligent tutoring is to let a learner reach a specific learning outcome within the shortest time and least effort possible, while at the same time keeping the learner motivated. To effectively reach this goal, an accurate evaluation of a learner's progress within an intelligent tutoring system is crucial in order to optimize learning content towards a learner's needs. This thesis presents Eagle Eye, a sensitive progress measure which is easy to interpret by both human and machine. Eagle Eye has been implemented and tested in a goal-based intelligent tutoring system that aims to improve self-management skills of children with type 1 diabetes. Initial results indicate that Eagle Eye's output enables human experts to evaluate a child's progress and use that evaluation to ensure optimal learning.

Acknowledgements

For the realization of this thesis I would like to gratefully acknowledge the following people.

My company supervisor Mark Neerincx, thank you for your valuable input and provocative discussions that clearly optimized my learning path during the thesis period.

My company supervisor Willeke van Vught, thank you for helping to get up to speed in the beginning of the thesis project, for your insights regarding the PAL project and for sharing your very to-the-point feedback on draft versions of this thesis.

My university supervisor Gerard Vreeswijk, thank you for elaborately taking the time to discuss mathematical ideas, for showing me how to sharpen my writing skills and for your extended feedback on the draft versions of this thesis.

My roommate at TNO Soesterberg, Jan, thank you for the enjoyable times at TNO. Besides your very helpful mathematical insights, your witty remarks and our cooperative discussions about the technical parts of PAL, I appreciated the unwinding table tennis games in between the hard work.

All other interns at TNO Soesterberg, thank you for the good vibes. I will not forget the games of volleyball and table tennis in the garden of TNO. It was very nice that we were all in the same boat and that we could share experiences about our successes and frustrations.

A special thanks goes to my girlfriend Anna, thank you for your infinite support, love and willingness to proofread even the nerdier parts of this thesis. And finally, to our cats Pippi and Socrates for the appreciative listening to my technical monologues and the uplifting cuddles during the typing work.

This research is part of the PAL project, which is funded by the European Union in the Horizon2020 program (ref. H2020-PHC-643783).

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Chapter 1

Introduction

1.1 General introduction

The field of intelligent tutoring becomes more important every year. The aim of intelligent tutoring is to let a learner reach a specific learning outcome within the shortest time and with the minimal effort, while at the same time keeping the learner motivated.

Challenging learning materials encourage learners to learn, as long as the materials are companioned with guidance [44]. However, a learner might give up if the learning materials provided are too challenging and, on the other hand, if the learning materials provided are too easy, a learner will become bored and will quit as well [16].

To keep a learner motivated, an intelligent tutoring system needs to optimally adapt its learning materials to the specific needs of a learner, while, at the same time, minimizing an individual's time and effort. Such optimal adaptation of a learner's learning path (i.e. a sequence of learning materials) is estimated based on an evaluation of a learner's progress with a progress measure [32, 36].

This research focuses on the creation of a progress measure of which the results are interpretable by both humans and machines. Human interpretability ensures that human experts are able to evaluate a learner's progress and, if needed, optimize the learning materials based on this evaluation. Machine interpretability enables computers to, on the basis of the output of such progress measure, automatically detect a learner's characteristics and preferences.

To that end, this research proposes a progress measure called Eagle Eye. Within Eagle Eye, progress is calculated based on the average number of attempts learners generally need to successfully solve a learning task. Furthermore, for the progress calculations the difficulty of a learning task, which is set by a human expert, is taken into account.

This research is conducted within the context of the PAL (Personal Assistant for healthy Lifestyle) project. The PAL project is led by TNO (the Dutch organization for Applied Sciences) together with multiple partners throughout Europe. The aim of the PAL project is to develop an intelligent tutoring system, called the PAL system, aimed to teach children with diabetes type 1 self-management skills. Education within the PAL system is goal-based. A child that participates in a PAL experiment will together with its parents and a health-care professional decide what diabetes-related goals a child will pursue. The health-care professional then activates these goals in the PAL system. Within the context of PAL, health-care professionals are responsible for (i) evaluation of a child's progress and (ii) (if necessary) adjustment of a child's goal selection to optimize their learning.

Since the development of Eagle Eye takes place in the context of the PAL system, Eagle Eye is tailored to the PAL use case. Eagle Eye's higher aim is to support health-care professionals to successfully evaluate a child's learning progress and, if needed, optimize a child's goal-setting based on this evaluation. For validation purposes, (i) semi-structured interviews have been conducted with multiple health-care professionals in order to determine if Eagle Eye does indeed provide those health-care professionals with the information needed to evaluate a child's progress and, if necessary, to act upon this evaluation and (ii) the current progress measure is qualitatively compared with Eagle Eye.

This introduction concludes with an overview of the research problem and relevance of this study. Chapter two provides an overview of current literature related to measuring progress in the context of intelligent tutoring systems. Chapter three discusses the PAL use case, including certain design constraints that the PAL use case brings along. In chapter four, the author proposes a new progress measure called Eagle Eye, which takes into account the open problems as found in current literature as set out in chapter two and the PAL design constraints as outlined in chapter three. Chapter five describes the method that has been utilized to validate if Eagle Eye can be used successfully by human experts. Chapter six discusses the results that follow from the application of that method. Chapter seven concludes with an overall conclusion and discussion of results, research limitations and openings for future research.

1.2 Problem statement

This study focuses on intelligent tutoring systems, which (i) provide educational activities (e.g. quiz questions, videos, sorting and memory games) that center on a personalized set of learning goals, and (ii) continuously collect data regarding performance, knowledge, user experience and context.

A learner's progress regarding goal-driven knowledge and skill acquisition in such a system should be classified by Eagle Eye in such a way that human experts can easily identify relevant characteristics of a learner's learning process. This identification should help the learning coaches (i) to evaluate a learner's learning process and (ii) to adapt the setting of learning goals for an individual learner to improve the learner's learning results. The research question is:

- How should progress in relation to goal-driven educational activities, offered to learners on a digital device, be calculated on the basis of a learner's performance, knowledge, user experience and context data in such a way that the human expert ("health-care professional") can improve goal-setting?

1.3 Research relevance

The research conducted in this thesis and Eagle Eye, the progress measure proposed in this research, contribute to the scientific field of artificial intelligence for the following reasons:

1. A precise progress measure could be utilized to asses a learner's current situation within an intelligent tutoring system and to intelligently predict a learner's future results given a specific learning path.

2. Output of such a precise progress measure can be utilized to derive which learning paths are effective for which type of learners.

3. The results that the progress measure provides for a specific learner can be utilized to classify a learner's progress, based on comparison of a learner's progress with other learner's progress.

4. The progress measure can be utilized to validate future optimizations (i.e. measurements can be used to validate other research).

Chapter 2

Related literature

This chapter treats literate related to progress measures within the context of intelligent tutoring systems. Firstly, the main characteristics of what constitutes a progress measure are outlined. Secondly, this chapter will go into current approaches in literature towards measurement of progress and performance within intelligent tutoring systems. This chapter will conclude with an overview of the main unsolved problems encountered in literature regarding progress measures within the context of intelligent tutoring systems.

2.1 Definition of progress measurement

Measuring a learner's progress within an intelligent tutoring system (ITS) is important to be able to adapt the learning content to a learner's needs which will ultimately maximize the probability that a learner achieves its learning goals. An ITS can be defined as a computer-based learning system that utilizes (i) knowledge models that specify learning materials and (ii) strategies regarding how to teach those knowledge models. A progress measure within the context of ITS serves two goals.

Firstly, an ITS utilizes a progress measure to make inferences about a learner's ability, in order to dynamically adapt the learning content or style of instruction towards the preferences of such learner [39, 46]. Depending on the type of ITS, such adaptation can be executed either automatically by a computer (called automated intervention) or manually by a human learning expert [8]. In the latter case, based on the results of a progress measure, a human learning expert can evaluate a learner's progress and adapt the ITS course materials accordingly to ensure that a learner successfully achieves its learning goals [7]. E.g. a human learning expert can assess a learner's system engagement to ensure that a learner stays motivated, as motivation is an essential prerequisite to attain learning goals [17].

Secondly, with help of a progress measure, it is possible to determine if the learning system results in an increase of a learner's knowledge and skill level and thus in a learner's ability over time [5].

As illustrated in Figure 2.1, the input of a progress measure always exists of observations of a learner's performance from an ITS. The way a progress measure reports the output is dependent on the secondary goals of a progress measure. Examples of such secondary goals include estimation of a learner's learning preferences, discovery of a learner's latent characteristics and optimization of a learner's learning process within an intelligent tutoring system [9].

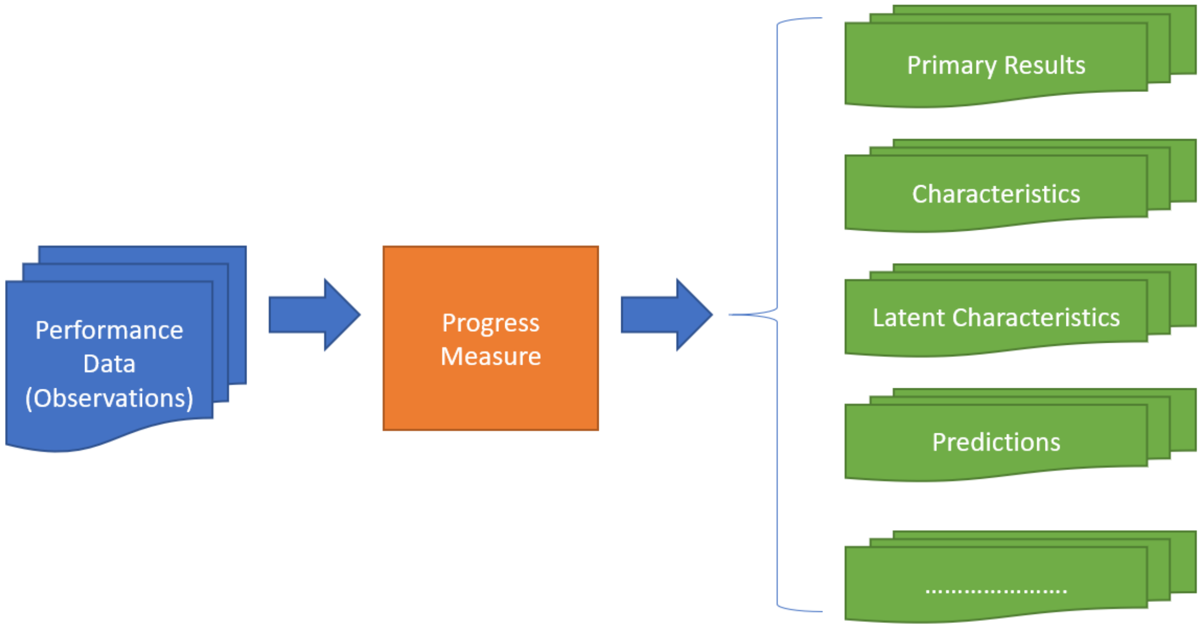


Figure 2.1 Progress Measure Output Diagram
The input of a progress measure in the context of intelligent tutoring systems exists of observations of a learner's performance. Depending on the type of progress measure, a progress measure can produce different types of results.

2.2 Current approaches towards progress measurement

Literature describes multiple approaches to measure a learner's progress within an ITS, which are roughly based on extensions, variations and combinations of two main theories. The first main theory is the Item Response Theory, that postulates that a learner's ability can be derived from the statistical relationship between the difficulty of a learning problem and a learner's performance [5]. The second main theory is Student Modeling, a theory that estimates a learner's performance based on a series of that learner's answers to learning problems [2]. Student Modeling knows two computational approaches, being the more dominant Bayesian Knowledge Tracing [36] and the more recently invented approach of Deep Knowledge Tracing [24].

2.2.1 Item Response Theory

Measuring a learner's ability at a certain moment in time is a challenge, because a learner's ability is an unobservable variable (also known as a latent variable). Unlike for example a learner's height and weight, a learner's ability cannot be measured directly. Examples of such abilities are reading skills, mathematical skills and intelligence in general [5]. The challenge of the unobservable ability variable is solved by Item Response Theory by probabilistically relating ability to a learner's performance in relation to a learning task. Within the context of Item Response Theory, a learning task is a question that tests a specific facet of the ability of interest. Item Response Theory states that the probability that a learner answers a learning problem correctly can be modeled as a function of a learner's ability. Therefore, each learning task is simplified to three parameters:

- **Difficulty** (b): the difficulty of a learning problem is expressed as a number on the same scale as a learner's ability. The difficulty value of a learning problem matches with the ability value of learners that have a 50% probability of answering that learning problem correctly.
- **Discriminatory value** (a): this parameter states to which extent a learning problem can discriminate between learners that have an ability value below the difficulty value of the learning problem on the one hand and learners that have an ability value above the difficulty value on the other hand.
- **Guessing parameter** (c): this parameter represents the probability that a learner guesses the answer to a learning problem correctly without actually knowing the answer.

The statistical relationship between a learning problem and the value of a learner's ability θ can, taking into account the three parameters described above, be modeled by means of different types of mathematical functions, e.g. sigmoid function [6, 18].

Item Response Theory models the relation between a learner's ability and a learning problem based on three assumptions:

- each learning problem has a unique difficulty value, which is constant,
- because not all learners have the same ability, all learners can have a unique ability value, and
- the ability value of learner θ is constant. Thus, a fluctuating ability value cannot be modeled in basic Item Response Theory.

2.2.2 Student Modeling

While Item Response Theory assumes that a learner's ability value θ is constant, Student Modeling assumes that a learners' ability value fluctuates over time. Student Modeling estimates a learner's ability value at timepoint τ based on the answers that such learner has provided to learning problems prior to timepoint τ [15]. A Student Model is a statistical model that can estimate a learner's performance in relation to a certain learning problem, taking into account the learner's performance history. To enable the Student Model to accurately estimate a learner's performance in relation to future learning problems, the Student Model is trained and tested with performance data of learners using a supervised learning method.

Student Modeling knows the following assumptions/constraints:

- **Ability θ is dynamic**: unlike Item Response Theory, Student Modeling assumes that a learner's ability value θ is a variable that changes over time,
- **No student diversity**: a Student Model does not discriminate between characteristics of different learners and thus a Student Model treats each learner equally [25],
- **No content diversity**: specific properties of a learning problem, such as difficulty level or learning problem type, are not taken into account [18], and
- **No forgetting**: also called all-or-none human learning, a Student Model assumes that once a learner has learned a skill, the learner will not forget about that skill [25].

Bayesian Knowledge Tracing

Bayesian Knowledge Tracing is a computational approach for Student Modeling, based on a hidden Markov model. After the introduction of Bayesian Knowledge Tracing by Corbett and Anderson [15], Bayesian Knowledge Tracing has been widely applied to different intelligent tutoring systems [41, 23] which lead to the identification of some fundamental problems regarding Bayesian Knowledge Tracing, such as the following:

- **Local Maxima Problem:** Bayesian Knowledge Tracing learns four parameters from the train set. The parameter values that result from such learning are the values that together result in the best estimations of X_{st+1} in the train set. However, because of the immense size of the search space, not all combinations of parameter values can be investigated. Therefore, the resulting parameter set is possibly not the most optimal set, but a set that is trained to a local maximum instead of the global maximum [41].
- **Identifiability Problem:** occurs if different sets of parameter values can produce the best estimations of X_{st+1} in the train set. If this is the case, it is not possible to identify which set of parameters reflects the most optimal Student Model [10].

- **Binary understanding:** according to Bayesian Knowledge Tracing, a learner either masters a skill or not. Some researchers are of the view that this dichotomous perspective is unrealistic [36].

- **Ignorance of confounding factors:** Bayesian Knowledge Tracing does not distinguish between any learner or problem specific information. Therefore, it ignores possible confounding factors on performance [25].

Deep Knowledge Tracing

The more recently introduced computational approach for Student Modeling is Deep Knowledge Tracing, which utilizes Recurrent Neural Networks as a Student Model [36]. Although the results of Deep Knowledge Tracing look very promising [24], the following problems are identified by various scholars:

- **Human Interpretability**: Deep Knowledge Tracing utilizes multi-dimensional parameters which are not interpretable by humans [24, 47].

- **Large dataset required**: because Deep Knowledge Tracing utilizes multi-dimensional parameters, training needs more data than Bayesian Knowledge Tracing which utilizes just four scalar parameters [36].

- **Computationally intense**: Recurrent Neural Networks require more computational power than Bayesian Knowledge Tracing models. Furthermore, the authors of [47] compared Item Response Theory based models with Deep Knowledge Tracing models. For large datasets the authors were not able to train Deep Knowledge Tracing models as they were hampered by computational tractability. However, they were able to train models based on Item Response Theory for large datasets.

2.2.3 Combinations and extensions

Item Response Theory and Student Modeling both have strengths and weaknesses. In contemporary research a growing body of work has focused on combining both theories in order to improve the accuracy of Student Modeling and to include so called secondary data, e.g. including use of hints, response times and other characteristics. [25]

Multidimensional Item Response Theory

The authors of [18] extend Item Response Theory with a multi-dimensional variable θ of which each dimension tracks the ability of a learner for a specific skill. The authors yield a significant improvement in comparison to not utilizing the sensitivity of multiple skills. The authors state that their model can be extended by considering other observable events which likely have a correlation with skill improvement such as hints or learning aids.

Temporal Item Response Theory

Temporal Item Response Theory assumes that a learner's ability θ can change in between attempts. A learner could forget knowledge or acquire knowledge from outside the ITS. The process of forgetting and acquiring is modeled as a stochastic process (a Wiener process) varying over time. The change of θ between time t, θ_t and some future time $\theta_{t+\tau}$ is normally distributed with a mean of 0 and a variance of $\lambda^2\tau$. In this formula λ represents a smoothing parameter. See [47, 18, 20] for details.

Hierarchical Item Response Theory

Within many ITS different learning problems that belong to the same skill have properties which can be used to group the learning problems, e.g. learning problem type or topic. Hierarchical Item Response Theory extends Item Response Theory with the concept of a group. Each learning problem i is associated with a group $j(i)$. Hierarchical Item Response Theory assumes that different learning problems from the same group have assumed a similar difficulty level. [47] shows that Hierarchical Item Response Theory outperforms Deep Knowledge Tracing and basic Item Response Theory.

Difficulty-aware Student Modeling

In an attempt to integrate Bayesian Knowledge Tracing and Item Response Theory, the authors of [25, 20, 26] pose that Item Response Theory and Bayesian Knowledge Tracing correspond with each other regarding the effects of a learner's ability θ and a learning problem's difficulty b on the one side (Item Response Theory) and the effects of guess parameter G and slip parameter S on the other side (Bayesian Knowledge Tracing). The researchers conclude that the learning problem's difficulty is the strongest indicator for estimating a learner's future results [25].

2.3 Conclusion: open issues regarding progress measurement

As discussed above, different researchers looked at combinations of Student Modeling and Item Response Theory. Such combination could combine the strength of (i) Item Response Theory to statistically relate the outcome of an attempt of a specific learning problem to a specific ability value θ and (ii) Student Modeling to model the change of such ability over time. However, such approach entails a big parameter space, namely each learning problem and learner should be parameterized specifically, which leads to mathematical hard problems such as the local maxima problem and the identifiability problem. On the other hand, with Deep Knowledge Tracing such problems do not arise, but Deep Knowledge Tracing is not interpretable by humans. Thus, the combination of big parameter spaces and human interpretability seems to be an open issue.

Chapter 3

PAL use case

The validation of Eagle Eye is performed within the context of the PAL (a Personal Assistant for a healthy Lifestyle)-project.[1]. The intention of this chapter is to provide the reader with sufficient information about the PAL project in order to understand the use case and the design constraints resulting from that use case. Firstly, the general use case of PAL is introduced by discussing the question why children with T1DM need self-management skills and how the PAL system attempts to contribute to such need. Secondly, the framework that PAL utilizes to personalize its education and which plays an important role in the validation of Eagle Eye, is examined. Thirdly, a brief overview of related research that is also carried out within the context of the PAL project is considered. The chapter concludes with the design constraints that follow from the PAL use case.

3.1 Overview

The PAL system aims to support children with type 1 Diabetes mellitus (T1DM) to develop their self-management skills. TNO (the Dutch organization for Applied Sciences) together with multiple partners including Imperial College London, TU Delft, different hospitals and other parties, form the PAL project. [2] Each year an experiment is carried out that gathers data about how children interact with the PAL app (see below). The exact focus of each experiment differs per year. For each experiment, a group of T1DM children between 8 and 14 years old are recruited in the participating hospitals [30].

3.1.1 Diabetes Mellitus Type 1

Type 1 Diabetes Mellitus is an autoimmune disease that is characterized by a low insulin production. Insulin is a hormone necessary to transport glucose from the bloodstream to the

[1] www.pal4u.eu

[2] For a complete overview of partners in the PAL project, see http://www.pal4u.eu/index.php/partners-2/

different body cells where the glucose is turned into energy. People with Type 1 Diabetes Mellitus should keep their blood glucose level as stable as possible within an optimal range. A too high blood glucose level (hyperglycaemia) can cause damage to different body organs, which in turn could lead to complications like cardiovascular disease, eye diseases and nephropathy. A too low blood glucose level (hypoglycaemia) can cause loss of consciousness or even death. Keeping a stable blood glucose level is a complex and dynamic process, influenced by multiple factors like food ingestion, type of food, stress and physical exercise. However, if diabetes is managed correctly, those complications can be delayed or even prevented [4].

3.1.2 Self-management skills

Children with Type 1 Diabetes Mellitus and their social environment need specific skills and knowledge in order to keep their blood glucose level as stable as possible. Examples of such skills and knowledge are (i) blood glucose measurement, (ii) counting of carbohydrates, (iii) determining the needed insulin based on amount of food, mental stress, physical exercise and hormones and (iv) administering the insulin [29]. An important part of self-management involves the activities related to the adjustment of the insulin dosage [38].

3.1.3 PAL System

The PAL system aims to support children with T1DM to learn self-management skills through goal-based education with a social robot (NAO) and its digital avatar. At the first visit of child in the hospital, a child together with its parents and a health-care professional decide what diabetes-related goals should be selected for a child to pursuit. The health-care professional then activates the selected goals in the PAL system. At the same visit, a child meets the social robot. At the end of the first visit, a child receives an Android Tablet with a PAL app. The PAL app contains a digital avatar of the robot and is the tool for a child to complete tasks. By successfully completing tasks related to a goal, a child can complete an active goal. Examples of such tasks are answering a few quiz questions, playing a memory game or writing something in the digital diary (implemented as a timeline) [35].

At certain intervals, for example every month, a child, a child's parents and the health-care professional meet again to evaluate that child's progress related to the active goals. Based on such evaluation it can be decided to change the selection of active goals in order to adapt to a child's needs (e.g. to enhance a child's motivation).

PAL consists of the following components: (i) a social robot and its digital avatar to help children achieve diabetes-related goals and (ii) different tools to monitor and adapt such diabetes-related goals by health-care professionals. See Figure 3.1 for a schematic overview of the system. Different research has shown that the social robot employed by PAL is able to motivate children to complete tasks and achieve the active goals [11, 22, 42].

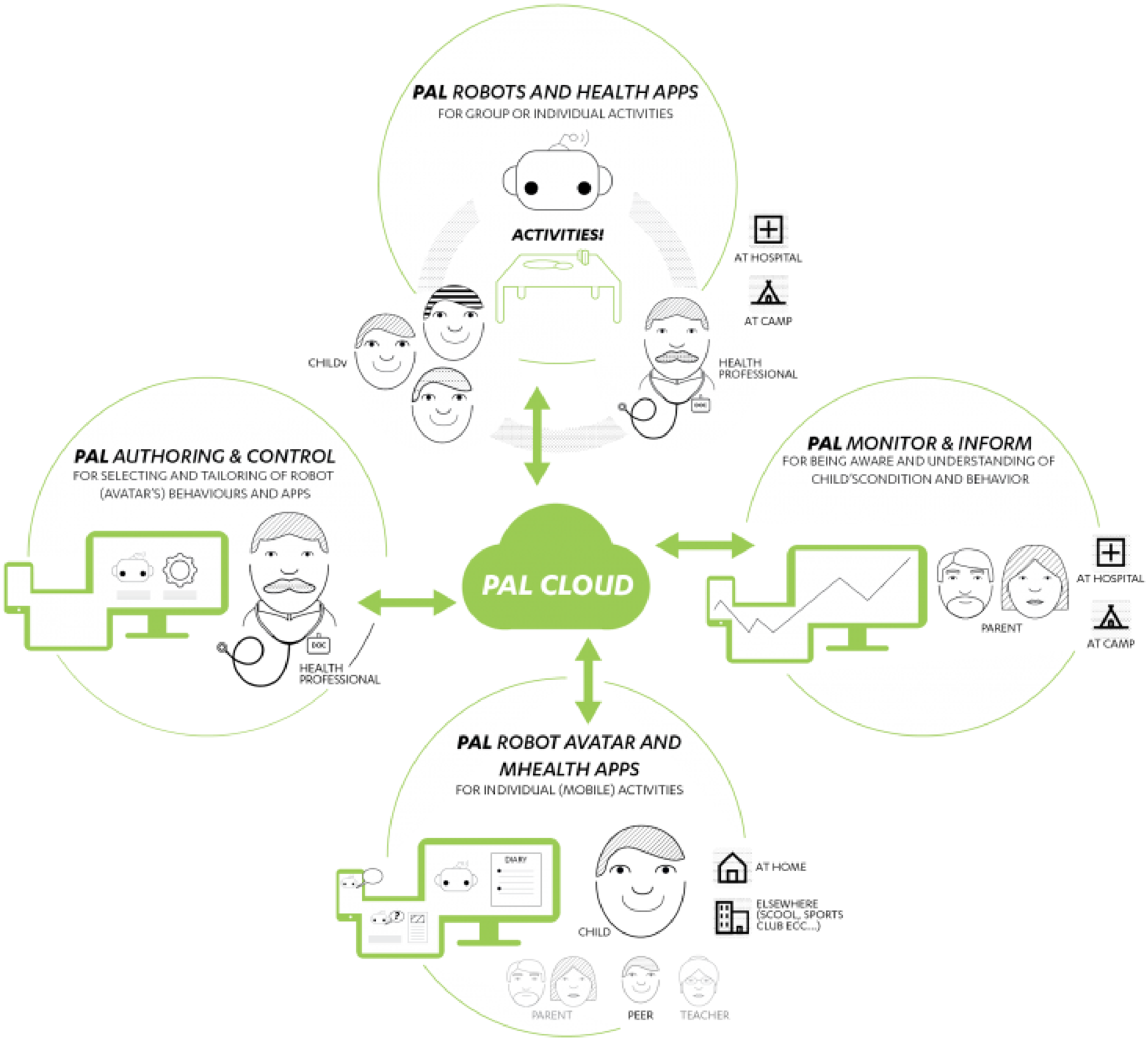


Figure 3.1 Components of the PAL system

3.2 PAL as intelligent tutoring system

Each child has different educational needs regarding self-management skills, therefore PAL utilizes a framework that divided the learning content over different goals. A child only encounters tasks in the PAL app that belong to active goals. As stated before, goals can be activated and deactivated by a participating health-care professional.

Framework for personalization

The PAL use case utilizes a framework of concepts to structure its educational content and to enable personalization. The goal framework corresponds with Midgley's achievement goal theory [31]. Within PAL the framework is formalized in an ontology as illustrated in Figure 3.2.

A *Learning Task* refers to a learning problem that a child should solve in order to complete a *Learning Goal*. An *Achievement* can be obtained if a child successfully (i) completes all Goals and (ii) collected all Achievements, related to such Achievement.

The following part contains some examples of Learning Tasks, Learning Goals and Achievements to provide the reader with a sound understanding of the ontology. Learning Goals are related to different facets of self-management within the context of T1DM. All Learning Goals have a name and a description. The following list presents a few examples of Learning Goals with their description.

- *No blame:* know that not he/she, nor anybody else, is to blame that he/she has diabetes.
- *Cause:* know that nobody knows why some people have diabetes, and some others do not.
- *Chronic:* know that diabetes is a chronic disease and will not go away.
- *Contagious:* know that diabetes is not contagious.
- *Food and Activity:* know the relationship between insulin, nutrition and physical activity.

The Learning Goal *Food and Activity* is obtained by a child, if a child completes following three Learning Tasks successfully:

- *Quiz Question*: correctly answer a quiz questions on why glucose measurement is needed.
- *Timeline activity:* add a general activity to the diary.
- *Timeline activity:* add a sports activity to the diary.

If a child completes Learning Goals *No Blame*, *Cause*, *Chronic* and *Contagious*, then a child obtains achievement *Novice Diabetes*.

PAL's current progress measure (CPM)

The current progress measure (CPM) in the PAL system is available for health-care professionals. A health-care professional can login into the PAL system to obtain a child's current progress. The historical change of progress over time cannot be obtained.

CPM specifies a progress percentage for every active goal, achievement and learning task. CPM calculates progress as follows:

- *Learning task*: progress is either 100% if a learning task is successfully completed, 0% otherwise.
- *Goal:* progress is equal to the number of successfully completed tasks required for a goal, divided by the total number of tasks required for a goal.
- *Achievement:* progress of an achievement is equal to the number of completed required goals divided by the total number of goals required to attain an achievement.

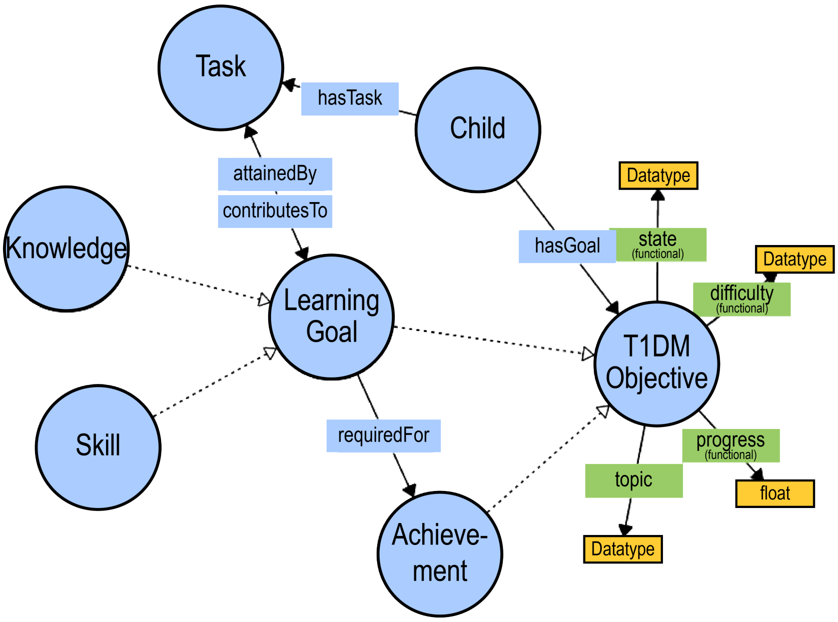


Figure 3.2 Ontology in PAL use case [35, p.3].

3.3 Trace data within PAL

Trace data results from children that use the PAL app during an experiment, and describes the behavior of children within the PAL app. Every year a different experiment is conducted, that could include specific Learning Goals, types of Learning Tasks and Achievements. Trace data logged within a PAL experiment, resides in different sources. Each source accommodates a different types of information. What follows is an overview of those sources and a description of their contents. See for a condense overview of the available trace data per data source Table 3.1.

- **Recorder Data**: collection of log files in plain text that describe the interactions between the PAL app and back-end, called the PAL cloud (see Figure 3.1). A child's system interactions within one session, result in exactly one log file in this collection. A session starts when a child logs in to the PAL app and ends if a child closes the PAL app. Types of information that are logged into the recorder data are the conversation between the child and the avatar, movements of the avatar and Learning Tasks that a child executes. See Figure 3.3 for an example part of a recorder file.

- **Ontology**: describes the relations between concepts within the PAL use-case as discussed in Section 3.2. See Figure 3.3 for an example part of an ontology file.

- **Tuple Data**: contains all the instances of the ontology. That includes the information of what goals are active for what child a particular time. The format of the tuple data is OWL [3] extended with a timestamp [34, 40]. See Figure 3.5 for an example part of a tuple file.

[3]See https://www.w3.org/TR/owl-features/ for the OWL Web Ontology Language Overview

- **QuestionsDB**: contains information about which quiz questions belong to which goals. See Figure 3.6 for a short selection of a QuestionsDB file.

```
REC|1496222029152|SystemInfo(id:HAMMER-0, content:i_am_ready)
2017-05-31 11:13:49,153 DEBUG: ps.PSClient - Serializing pal.TECS.SystemInfo
2017-05-31 11:13:49,153 DEBUG: ps.PSClient - Sending to .* via channel SystemInfo 46b data
REC|1496222029658|PushRequest(id:9003, data:[])
REC|1496222250030|LowLevelNaoCommand(id:BehaviorManager-48, command:actualposture;stand)
REC|1496222250030|LowLevelNaoCommand(id:BehaviorManager-67, command:blink;16777215;2236962;0.1;)
REC|1496222260345|GameMoves(id:9152, textToSpeak:finish;, typeOfAction:watch, startposition:[0, 0], endposition:[0, 0], timeInSec:0.0)
REC|1496222260345|SystemInfo(id:9153, content:GAME_FINISHED;30)
```

Figure 3.3 Recorder log example
Example of a few lines of a recorder log.

```
<edu:AmountGlucose> <edu:label> "Hoeveelheid Glucose"@nl .
<edu:AmountGlucose> <edu:label> "Zucchero e ipoglicemia"@it .
<edu:AmountGlucose> <edu:shortCode> "H4"^^<http://www.w3.org/2001/XMLSchema#string> .
<edu:AmountGlucose> <http://www.w3.org/1999/02/22-rdf-syntax-ns#type> <edu:LearningGoalType> .
<edu:AnswerA2> <edu:description> "Beantwoord alle quizvragen over voeding en activiteit goed"@nl .
<edu:AnswerA2> <edu:description> "Correctly answer all quiz questions with topic 'Activity' and goal 'A2'"@en .
<edu:AnswerA2> <edu:description> "Risposta corretta a tutte le domande dell'argomento !Attivit\u00E0\" e goal \"A2\""@it .
<edu:AnswerA2> <edu:hasGoalType> <edu:FoodAndActivity> .
<edu:AnswerA2> <edu:label> "Answer A2"@en .
<edu:AnswerA2> <edu:label> "Beantwoord A2"@nl .
<edu:AnswerA2> <edu:label> "Risposta A2"@it .
<edu:AnswerA2> <edu:numOfQuestions> "1"^^<http://www.w3.org/2001/XMLSchema#int> .
```

Figure 3.4 Ontology format example
Example of a few lines of the ontology.

```
<rifca:Quiz11cc9bf1_1358> <dom:status> "question_read"^^<xsd:string> "1494947484475"^^<xsd:long> .
<rifca:Quiz11cc9bf1_1358> <dom:status> "wait_for_robot_answers_read"^^<xsd:string> "1494947484478"^^<xsd:long> .
<dom:QuizHistory11d05c0a_1378> <rdf:type> <dom:QuizHistory> "1494947486730"^^<xsd:long> .
<dom:QuizHistory11d05c0a_1378> <dom:sessionId> "2"^^<xsd:int> "1494947486733"^^<xsd:long> .
<dom:QuizHistory11d05c0a_1378> <dom:turnId> "6"^^<xsd:int> "1494947486733"^^<xsd:long> .
<dom:QuizHistory11d05c0a_1378> <dom:roundId> "3"^^<xsd:int> "1494947486733"^^<xsd:long> .
<dom:QuizHistory11d05c0a_1378> <dom:asker> "0"^^<xsd:int> "1494947486733"^^<xsd:long> .
<dom:QuizHistory11d05c0a_1378> <dom:responder> "1"^^<xsd:int> "1494947486733"^^<xsd:long> .
<dom:QuizHistory11d05c0a_1378> <dom:questionId> "38"^^<xsd:int> "1494947486733"^^<xsd:long> .
<dom:QuizHistory11d05c0a_1378> <dom:answer> "149"^^<xsd:int> "1494947486733"^^<xsd:long> .
<dom:QuizHistory11d05c0a_1378> <dom:correct> "true"^^<xsd:boolean> "1494947486733"^^<xsd:long> .
<dom:QuizHistory11d05c0a_1378> <dom:hasChildId> <rifca:Childfce6d352_25> "1494947486733"^^<xsd:long> .
```

Figure 3.5 Tuple data format example
Example of a few lines of the tuple data.

```
are there carbs in chees;Zitten er koolhydraten in kaas;Ci sono i carboidrati nel formaggio;98;Nutrition;2;CC2, HTH2
are there carbs in meat;Zitten er koolhydraten in vlees;Ci sono carboidrati nella carne;96;Nutrition;3;CC3
are there carbs in meat?;Zitten er koolhydraten in vlees?;Ci sono carboidrati nella carne?;96;Nutrition;3;CC3
are there carbs in snap beans;Zitten er koolhydraten in spercibonen;Ci sono i carboidrati nei fagioli in scatola;99;Nutrition;2;CC2, HTH2
Are you allowed to eat everything when you have diabetes;Mag je alles eten als je diabetes hebt;NA;147;Diabetes general;3;HTH2, RS3, EC4
At which value do you have a hyper;Bij welke waarde heb je een hyper;NA;149;Hypos-Hypers;3;RAHR3, IM3
Can diabetes type 1 go away over the years?;Kan diabetes (type 1) overgaan?;NA;206;Diabetes general;1;BPK1
```

Figure 3.6 QuestionsDB Format Example
Example of a few lines of the QuestionsDB. Each column is separated by a semicolon. First column is the question in English, second column is the question in Dutch, third column is the question in Italian, fourth column is a question identifier, fifth column is a goal identifier, sixth column is a difficulty level and last column refers to the related achievements.

At the moment of research, the PAL use-case is its fourth year of the project. The trace data is available from the experiments held in year one, year two and from a 'special' experiment which

Table 3.1 Overview of variables per data source

Source:	Recorder data	Tuple Data	Ontology	QuestionsDB
Achievement entity	-	●	●	-
Goal entity	-	●	●	-
LearningTask entity	-	●	●	-
Child	●	●	-	-
Active Achievements	-	●	-	-
Active Goals	-	●	-	-
Active LearningTasks	-	●	-	-
Timestamp	●	●	-	-
Quiz question ID	◐	-	-	◐
Quiz question LearningTask	◐	-	-	◐
Quiz question Difficulty	-	-	-	◐
Quiz question Result	●	-	-	-
Quiz question Asker	●	-	-	-

● = yes; ◐ = sparingly; - = no;

is held during a holiday camp for children with T1DM. The difference between this special experiment and the experiments from previous years is that the special experiment was for a shorter period and children did not get personalized goals. Each year's experiment introduced new types of Learning tasks, as summed up below. See Table 3.2 for an exact overview of the available trace data for this research.

- **Year 1:** learning tasks include Quiz Questions and timeline related tasks.
- **Year 2:** learning tasks include a different set of Quiz Questions than year 1, timeline related tasks and a break-sort game.
- **Year 3:** learning tasks include all of year 2 extended with a memory game.
- **Year 4:** learning tasks include all of year 3 extended with video tasks.

3.4 Related research within PAL use case

Different research has been conducted within the PAL use case that is relevant to this research. Firstly, Lighthart [28] considered the relation between different type of avatars and the effect of such avatar on the motivation of the children. The author hypothesizes that, although motivation is a psychological construct which cannot be measured directly, the amount of such motivation can be obtained by two performance measures: (i) the amount of interaction with the PAL

Table 3.2 Overview of experiments and available data

Experiment:	Year 1		Year 2		Year 3	
Language:	IT	NL	IT	NL	IT	NL
Experiment carried out	●	●	●	●	-	●
Goal data available	-	●	-	●	-	-
Quiz questions	●	●	●	●	-	●
Break and sort	-	-	●	●	-	●
Memory	-	-	-	-	-	-
Timeline tasks	◐	◐	◐	◐	-	◐
Video	-	-	-	-	-	-

● = Yes; ◐ = Unknown; - = no;

system and (ii) the consistency between such interactions. The amount of interaction with the PAL system is the sum of all activities, measurements, pictures and goals that are added to the system by a child. Consistency is a measure based on the average amount of days between interactions with the PAL system by a child. A low average results in a high consistency and the other way around.

Secondly, Schadenberg [37] utilized an intelligent tutoring system with a NAO robot to research if personalization of a game's difficulty to a child's ability enhances a child's motivation to play such game. Therefore, the game's items have a difficulty level which is either easy, moderate or difficult. The system starts with moderate items. In case a child answers less than 70% of the moderate items correctly, the systems changes to easy items. Otherwise, if a child answers more than 80% of the moderate items correctly, the system changes to difficult items. The author concludes that the system was not capable to challenge a child optimally, but the underlying Bayesian rating system is suited to measure a child's performance.

Finally, Boelhouwer [12] considered patterns in children's system usage of the PAL system. According to the author, three different trends are observable such usage namely (i) children that use the system in the beginning and decrease their interaction over time. (ii) children that use the system in the beginning of the experiment and at the end and (iii) a small group of children that use the system constantly.

3.5 Design constraints

The improved progress measure should fulfill a few requirements which are either dictated by the PAL system (the progress measure should fit to PAL's goal framework) or originated from the various discussions with the company supervisors.

- **Fit to PAL's goal framework:** unlike some other intelligent tutoring systems that can produce infinite variations of the same learning tasks, PAL utilizes a strict set of Learning Tasks that have to be completed to achieve a goal. The progress measure should be able to fit on such system.

- **Human interpretability:** the result of the progress measure should be interpretable by the health-care professionals. That is, health-care professionals should be able to evaluate the progress of a child in such a way that a health-care professional can decide if the selection of active goals of a child should be adapted.

- **Computer interpretability:** the result of the progress measure should be interpretable by a computer. In research outside of the scope of this thesis, the results of the new progress measure should be usable to build a classifier upon (e.g. to classify results to certain learner characteristics).

Chapter 4

Proposed progress measure: Eagle Eye

The previous two chapters treat the design constraints (Section 3.5) that the PAL use case brings along and the open issues as set out in current literature (Section 2.3). Taking that information into consideration, the author proposes a new type of progress measure called Eagle Eye. In this chapter, firstly the considerations behind proposing Eagle Eye as a new progress measure are set out. Secondly, the technical details of implementing Eagle Eye are described. Finally, an overview of assumptions and restrictions is provided.

4.1 Improvement compared to PAL's current progress measure

Considering the research question of this thesis, Eagle Eye should calculate a learner's progress in relation to usage of an intelligent tutoring system that utilizes goal-driven educational activities. A learner's progress should be calculated on the basis of a learner's performance, knowledge, user experience and context data in such a way that the human expert ("health-care professional") can improve the learner's goal-setting. PAL's current progress measure (CPM) utilized by the PAL system reports a learner's progress to health-care professionals by calculating a progress percentage for every active learning task, goal and achievement. The result of this calculation is a high-level value describing a learner's progress. See Section 3.2 for a detailed description. Eagle Eye's main goal is to improve this calculation in such a way that it results in a more in-depth insight into a learner's progress. Health-care professionals should be able to improve adjustment of goals on the basis of the information provided by Eagle Eye (when compared to the information provided by CPM). Other progress measures, as discussed in the literature section above, are based on either Item Response Theory, Student Modeling or a combination of both. Both theories contain interesting elements that can improve the way that progress is calculated within the PAL system (as will be explained in detail below). However, neither theories can be directly applied to the PAL system. Item Response Theory is interesting because it assumes that every learning problem has a specific difficulty value. As Item Response Theory also assumes that a learner's ability is constant, it can unfortunately not be applied to the PAL system as PAL assumes that a learner's ability can increase over time. An interesting element of Student Modeling is that it takes into account both successful and unsuccessful attempts in order to predict a learner's ability. However, also Student Modeling cannot be applied directly to the PAL system as Student Modeling assumes a pseudo-unlimited number of learning tasks while PAL makes use of a specific and limited set of learning tasks that should be solved successfully in order to achieve a certain goal. Besides the interesting elements of Item Response Theory and Student Modeling as described above, TNO's requirements have also been taken into account for the development of Eagle Eye. For a consideration of TNO's requirements see Section 3.5.

Each of the two above described interesting elements that follow from Item Response Theory and Student Modeling have resulted into a proposed element for implementation in Eagle Eye:

- **Learning tasks are unequal**: CPM treats the completion of all learning tasks equally. In case a learner needs to solve two learning tasks to attain a goal, of which one is difficult and takes a long time to solve and the other is easy and can be solved in an instant, then CPM reports a progress of 50% after a learner has solved any of the two learning tasks. The CPM does not consider the time invested by a learner and thus the difficulty of a learning task in the calculation of progress. The author expects that, in comparison to CPM, health-care professionals would get a better indication of the time that a learner has invested and still needs to attain a specific goal if the difficulty of learning tasks would be taken into account for the calculation of progress. A better indication of time would in turn lead to an augmented perception of a learner's progress which can lead to improved goal setting by health-care professionals.

  The motivation for this claim is threefold:

  1. Difficulty of a learning task provides for a good indication of the time needed to solve that learning task for the following reasons. Firstly, generally the response time for difficult learning tasks is higher than for easy learning tasks [43]. Secondly, Item Response Theory states that it is more probable that a learner fails a difficult learning task than an easy learning task [5]. This means that a difficult learning task generally requires more attempts than an easy learning task. And because each additional attempt requires time, it takes more time to fully solve a difficult learning task than an easy learning task.
  2. Humans are used to make time estimations based on progress bars that express a progress percentage. Progress bars in software systems are employed to report on the progress status of an ongoing task by showing a percentage within a bar that fills up over time. Users utilize a progress bar to estimate the amount of time that is still needed to complete the ongoing task [33]. Because progress bars are

omnipresent within software systems and thus most humans are familiar with making time estimations based on progress percentages, it would be valuable to create a progress measure that reports progress that is directly proportional to the amount of time that a learner has invested and is expected to require until finishing.

3. Because progress should be directly proportional to the amount of time that a learner has invested, the completion of learning tasks with the same difficulty level should result in the same progress (similarly, learning tasks with a higher difficulty should result in a higher progress and learning tasks with a lower difficulty should result in a lower progress). This corresponds with the ideas of [3]. In this paper the author attempts to define difficulty of challenges within games. The author argues that each challenge with the same difficulty should relate to the same type of progression within the game [3].

- **All learning activity leads to progress:** CPM only reports progress when a learning task is successfully completed. The CPM does not consider unsuccessful attempts of a learner in the calculation of progress. The author expects that, in comparison to CPM, health-care professionals would get a more nuanced impression of a learner's progress if unsuccessful attempts would be taken into account for the calculation of progress. Such nuanced impression of a learner's progress can lead to improved goal setting by health-care professionals. The above expectation is based upon the following three arguments:

  1. Student Modeling is a successful way to track the ability of a learner in intelligent tutoring systems. Student Modeling predicts a learner's ability based on all the learner's attempts (both successful and unsuccessful) [2]. Although Student Modeling cannot be implemented directly into the PAL framework, this element can be implemented in Eagle Eye.
  2. Learners learn from mistakes. With each unsuccessful attempt, a learner is one attempt closer to a successful attempt and thus a learner progresses towards the attainment of a goal. In other words, unsuccessful attempts can still enhance learning, as a learner is more likely to answer a question correctly at the next attempt [27].
  3. As indicated above, CPM does not provide information on unsuccessful attempts to health-care professionals. However, such behavior is important to observe, because it could indicate if a learner needs help with a specific learning task or if a learner is on its way to become frustrated [16].

In conclusion, just like the eye of an eagle can spot small movements on the ground [21, p.11], Eagle Eye should be able to spot small movements in goal progression. And thus, Eagle Eye should be more sensitive towards progress than CPM and provide health-care professionals with a clear view on a learner's progress so that the health-care professional can improve the learner's goal-setting.

4.2 Implementation of improvement

This section describes how the two improvements are each converted into a mathematical model, followed by how those two models are combined into one progress measure that forms Eagle Eye. Finally, a formal description is given of the output format of Eagle Eye.

4.2.1 Learning tasks are unequal

Within Eagle Eye some learning tasks contribute more than others to a learner's progress in relation to a specific goal. To quantify the weight of completion of a learning task in relation to progress, each learning task is labeled with a difficulty parameter. The difficulty parameter can be set manually, for example by a learning expert, or can be calculated automatically, for example on the basis of performance data. The difficulty parameter should adhere to the following properties, in order to base progress calculation upon it:

1. Learning tasks with the same difficulty value should be solvable in an equivalent amount of time and will thus result in equal progress towards the goal when solved [3].

2. Difficulty should represent the amount of time that is needed to solve a learning task. If a learning task is twice as difficult as another task, it should also take twice the amount of time to solve it correctly in comparison to that other task. If difficulty adheres to this property, then it can be concluded that twice the difficulty will result in twice the progress.

Taking the above properties as assumptions, difficulty can now be utilized to calculate progress. The following situation will serve as an example for progress calculation based on difficulty. If goal q can be attained by solving learning tasks 1, 2 and 3 and learning task 1 has difficulty 2 and learning tasks 2 and 3 have difficulty 1, then solving learning task 2 or 3 would result in the same progress (because of property 1). Furthermore, because learning task 1 is twice as difficult as learning task 2, then solving learning task 1 should result in twice the progress compared to the progress that results from solving learning task 2 (because of property 2). In conclusion, if a learner successfully solves a learning task, then a learner's progress in relation to a goal is proportional to the combined difficulty of the goal's learning tasks. See Figure 4.1 for an illustration and comparison with CPM.

Mathematical model

The theory set out above can be translated into a mathematical model based on the following definitions:

- $B_i \in \mathbb{R}_{\geq 0}$ refers to the difficulty value of learning task i, such that the difficulty value is a scalar value that adheres to the two properties described above.

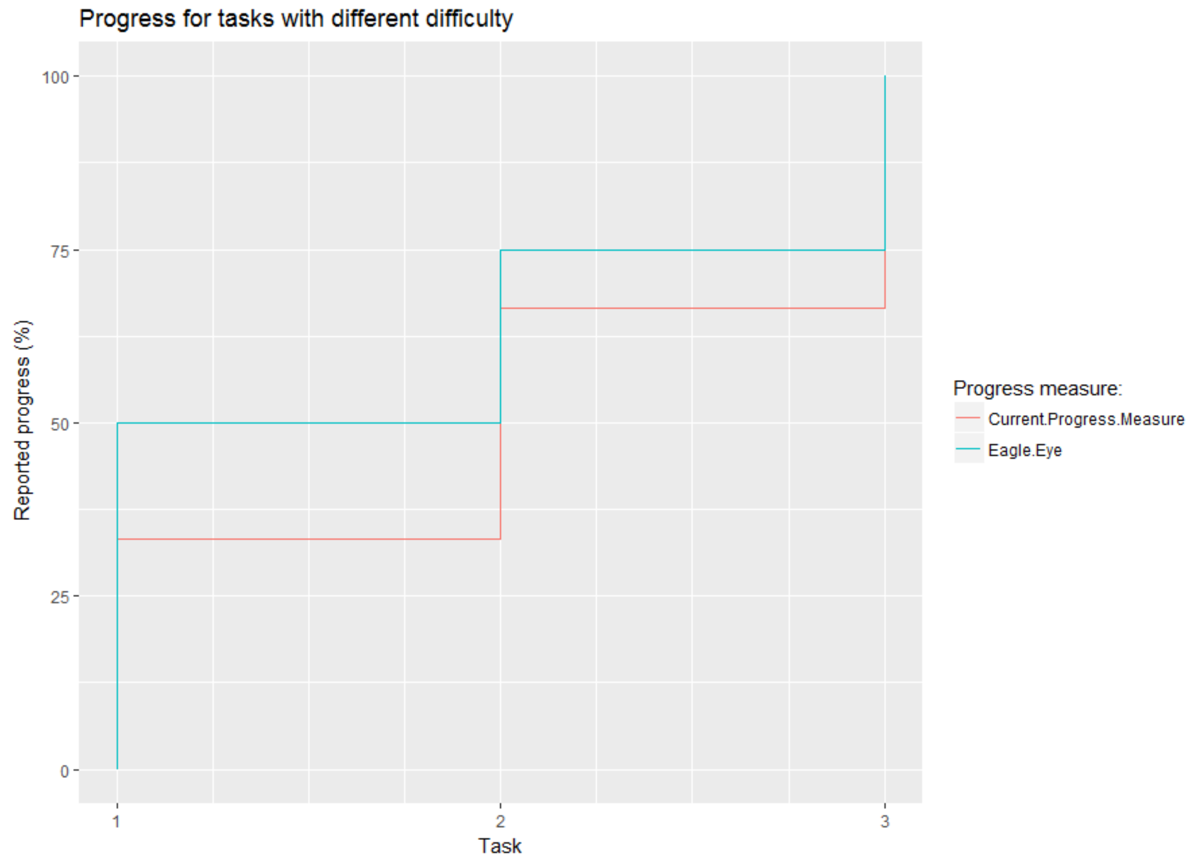


Figure 4.1 Progress in relation to learning tasks with different difficulty values
If task 1 is twice as difficult as task 2 and 3, than Eagle Eye reports 50% progress after solving task 1, while CPM reports 33.3% for the completion of each learning task.

- I_q forms the set of learning tasks i that all have to be completed successfully in order to achieve goal q.

- $B_q \in \mathbb{R}_{\geq 0}$ refers to the combined difficulty of goal q's learning tasks, which is equal to the sum of all difficulties of the learning tasks in the set I_q. See also Equation 4.1.

$$B_q = \sum_{i=1}^{|I_q|} B_i \tag{4.1}$$

A learner that completes a learning task i gets a progress increase proportional to difficulty value B_i. $d_{i\tau}$ refers to the attained difficulty value of learning task i. If a learner successfully solved learning task i before time interval τ, $d_{i\tau}$ is equal to B_i, otherwise $d_{i\tau} = 0$. Therefore, a learner's progress θ at time interval τ for a goal q is equal to the sum of difficulty values of learning tasks that a learner solved at time interval τ divided by the combined difficulty B_q. See Equation 4.2

$$\theta_{q\tau} = \frac{\sum_{i=1}^{|I_q|} d_{i\tau}}{B_q} \tag{4.2}$$

4.2.2 All learning activity leads to progress

Translating the second improvement to a mathematical model can be done in various ways. Based on multiple discussions with the company supervisors, it was concluded that an intuitive approach for reporting progress based on unsuccessful attempts can be illustrated by the following example. If the successful completion of a learning task i would result in a learner's progress of 20% in relation to a goal q, and that specific learner needs 4 attempts to successfully complete learning task i. Then for each unsuccessful attempt that learner's progress would increase by 5%. See Figure 4.2 for an illustration of such approach. This approach would result in a linear increase of progress of the attempts. However, the example is quiet hypothetical, as the number of attempts a learner needs to solve a specific learning task successfully is not known upfront. Therefore the exact amount that a learner's progress should increase for every attempt in order to have a linear increase cannot be known in advance. Thus, the 'perfect' case as illustrated in Figure 4.2 is not attainable. But, what can be known upfront is the average number of attempts learners need to solve a specific learning task. That number can be obtained from, for example, historical performance data. The average attempt rate can be utilized to calculate the progress for a learner. Eagle Eye follows the linear increase of progress until a learner's number of attempts are one below the average attempt rate. From that point, if a learner needs more attempts than average, the progress is increased only slightly. Eagle Eye only reports full progress for the learning task if a learning task is successfully solved. See Figure 4.3. An added advantage of this approach is that the progress curve reveals how a learner performs compared to an average learner. Namely, a learner that performs above average gets abrupt increases, a learner that performs like an average learner gets a linear increase (as illustrated in Figure 4.2) and slower learners get increases that start linear and end asymptotic (like illustrated in Figure 4.3).

Mathematical model

The theory set out above can be translated into a mathematical model as follows. Suppose that the successful completion of learning task i results in 20% progress in relation to a goal q. Furthermore, suppose that generally learners solve learning task i at the fifth attempt (so the average attempt rate (α_i) is 5). If a learner answers a learning task i correctly before time interval τ, the learner receives, at time interval τ, the complete progress that is related to this learning task (i.e. 20%). Otherwise, if a learner has tried but did not successfully solve a learning task i before time interval τ, then a learner attains only a part of the learning task's progress. The size

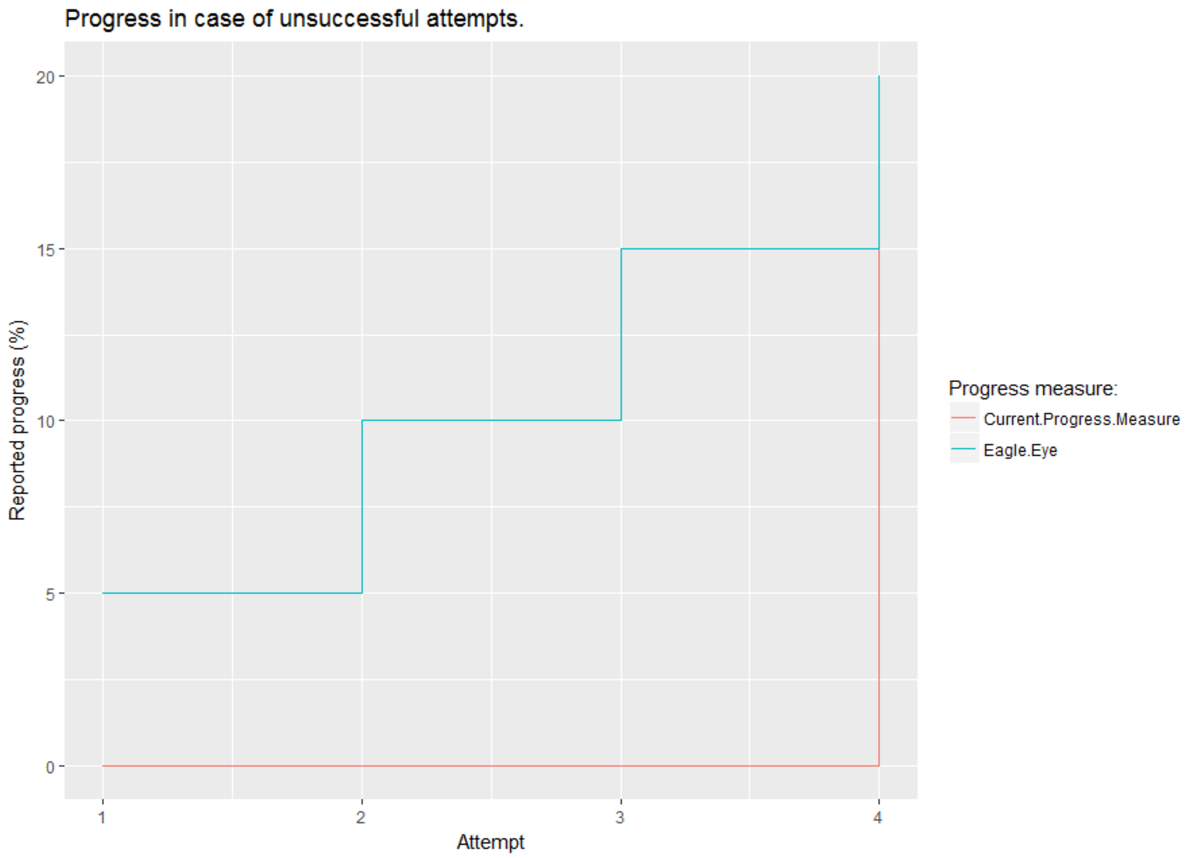


Figure 4.2 Progress in case of unsuccessful attempts
Case: a learning task in PAL contributes for 20% progress for a goal. A learner needs 4 times to solve the learning task. Eagle Eye would measure the unsuccessful attempts in the progress calculation, but the current progress measure only measures the successful attempt.

of the attained part depends on t, the number of attempts that a learner has made to solve the learning task.

- If t is smaller than the average number of attempts (α_i) that learners need to solve learning task i, the learner's progress for learning task i is equal to the complete progress related to this task (20%) divided by the average attempt rate α_i (5), multiplied by the actual number of attempts t. This way, if a learner behaves like an average learner and solves learning task i in α_i times, the learner's progress increase for learning task i is linear. In Figure 4.4, the red line illustrates this behavior.

- If t is equal to or higher than the average attempt rate α_i, a learners' attained difficulty increases after each attempt but it will not at any point reach the total progress of 20%. More specifically, the learner receives progress for this learning task that is equal to progress of the previous attempt increased by half of the difference between the previously attained progress and the total progress. In Figure 4.4, the blue line illustrates this behavior.

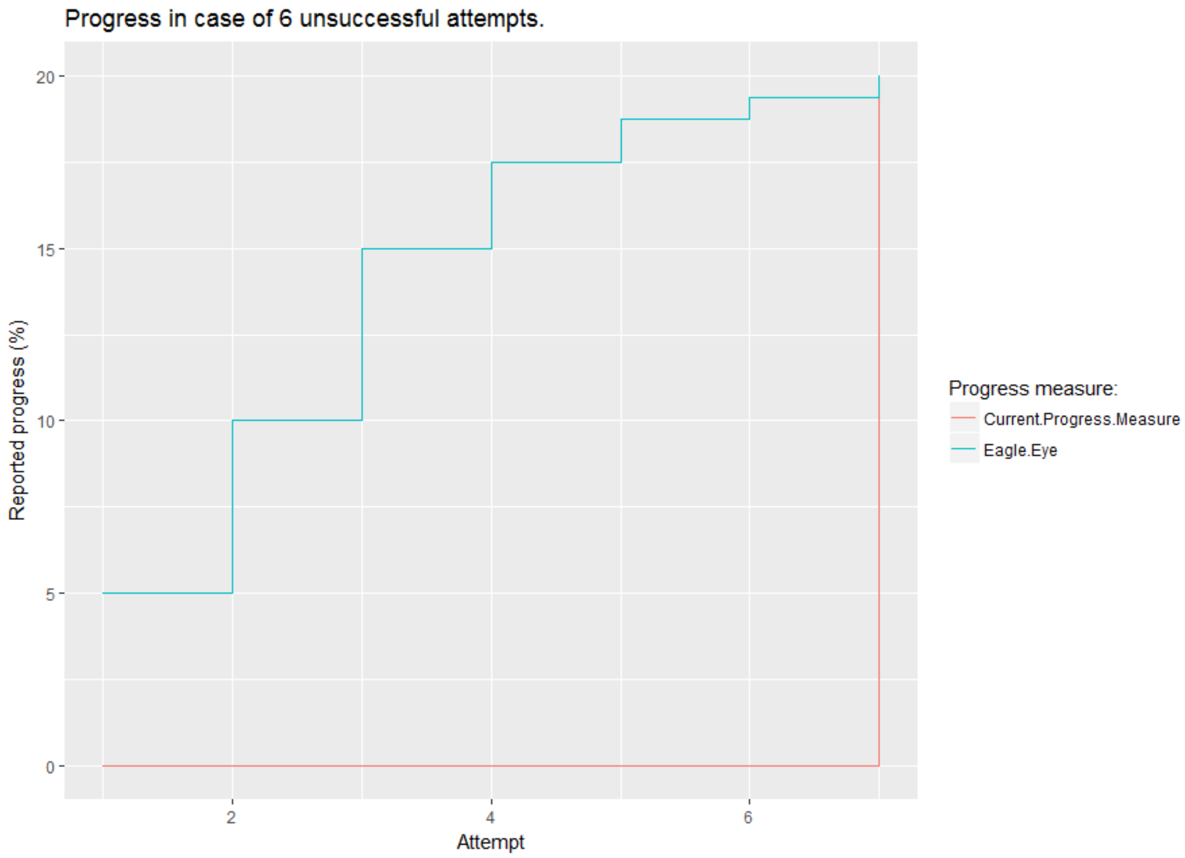


Figure 4.3 Progress in case of unsuccessful attempts
Case: a learning task in PAL contributes for 20% progress for a goal. A learner needs 4 times to solve the learning task on average. In this case the learner needs 7 attempts. Eagle Eye measures the unsuccessful attempts in the progress calculation, but the current progress measure only measures the successful attempt.

For the purpose of explanation, the equations that formalize the above model are threated in the next subsection.

4.2.3 Combining the two improvements

The two improvements can be easily combined into one model. As specified above, the first improvement states that the amount of a learner's progress in relation to a goal q that results from the successful completion of a learning task i depends on that learning task's difficulty B_i in relation to the combined difficulty B_q of goal q. The second improvement states a learner's progress in relation to a learning task i is only complete if a learner successfully completed learning task i. In case a learner tried but did not successfully solve learning task i, a learner's progress for learning task i is only part of the complete progress.

Progress can be calculated fully with the machinery of the first improvement (Equation 4.2 and 4.1). Only in case that a learner did attempt, but did not successfully completed one of

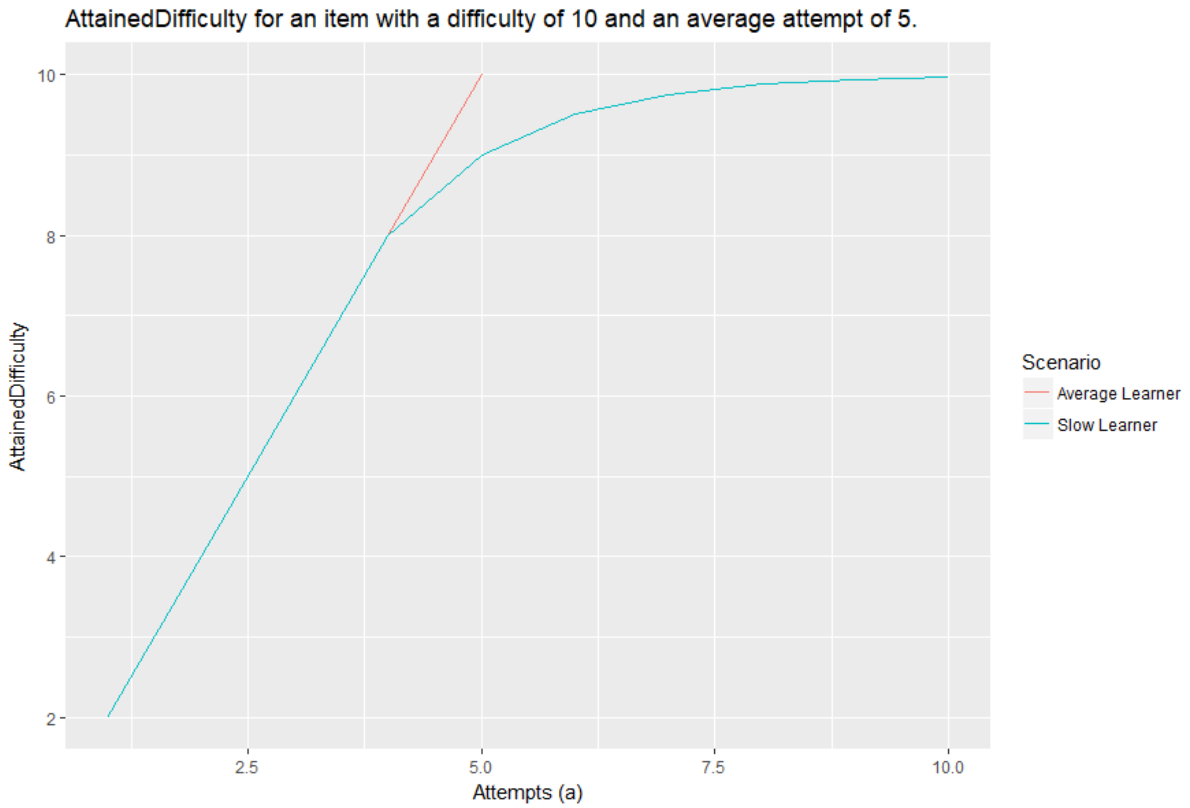


Figure 4.4 Graph of the function d_i
In this scenario the combination between the blue and red line represents the average learner. The blue curve represents learners that learn slower than average.

the learning tasks, the machinery of the second improvement is needed. This combination is applied as follows: for every wrong attempt at a learning task i, a learner 'attains' only a part of the learning task i's difficulty. This amount of attained difficulty (d_i) can then be utilized in the formula of the first improvement (Equation 4.2) to calculate the progress for a goal q. The value of d_i depends on the number of attempts t and the average attempt rate (α_i), as described above. In case a learner successfully completed learning task i, the attained difficulty d_i is equal to learning task i's difficulty B_i. See Equation 4.3.

$$d_{i\tau}(t,r) = \begin{cases} B_i, & \text{if } r = 1 \\ t\frac{B_i}{\alpha_i}, & \text{for } 0 \leq t < \lfloor \alpha_i \rfloor \\ (\lfloor \alpha_i \rfloor - 1)\frac{B_i}{\alpha_i} + \frac{2^{t-\lfloor \alpha_i \rfloor + 1} - 1}{2^{t-\lfloor \alpha_i \rfloor + 1}}\frac{B_i}{\alpha_i}, & \text{for } \lfloor \alpha_i \rfloor \leq t \end{cases} \tag{4.3}$$

Where:

- $t \in \mathbb{N}$: attempts, i.e. the number of attempts that a learner has made to solve learning task i.
- $r \in \{0,1\}$: result of the last attempt, a binary variable that is either 1 if correct or 0 otherwise.

- $B_i \in \mathbb{R}_{\geq 0}$: difficulty of learning task i.
- $\alpha_i \in \mathbb{R}_{\geq 0}$: average attempt rate, number of attempts that learners generally need to answer learning task i correctly.

Based on the above construction, a learner's progress in relation to a goal q can be calculated with Equation 4.2. Namely, a learner's progress at time interval τ in relation to a goal q is equal to the sum of attained difficulty $d_{i\tau}$ for all learning tasks in set I_q divided by the sum of the total difficulty for all learning tasks in set I_q.

Note: some learning tasks cannot be answered incorrectly. Such learning tasks can be either fulfilled or not, but they cannot be solved 'incorrectly'. Examples of such learning tasks are watching a video, sharing some type of information or carrying out a task outside of the context of the computer. These kinds of learning tasks can therefore not have an average attempt rate α. If a learner performs such a learning task, the learner attains the full difficulty of the task. See Equation 4.4.

$$d_{i\tau}(r) = \begin{cases} B_i, & \text{if } r = 1 \\ 0, & \text{if } r = 0 \end{cases} \tag{4.4}$$

4.2.4 Output: ability matrix

The output of Eagle Eye is a matrix P_s that describes the ability progress of a learner s over a specific period of time. Every column refers to a specific goal q which is an element of the total goal set Q. Goal set Q contains both active and inactive goals. A row in P_s describes the learner's complete knowledge state at a time interval τ as it contains a learner's ability θ in relation to each goal q in the goal set Q. $\theta_{q\tau}$ refers to a learner's ability θ for a goal q at a time interval τ.

The value of a learner's ability θ in relation to an active goal q at time interval τ is a decimal fraction between 0 and 1. Inactive goals are values at -1. A value $\theta_{q\tau} = 1$ means that a learner has 100% ability for a goal q at time interval τ. On the other hand, $\theta_{q\tau} = 0$ refers to a learner's ability of 0% for goal q at time interval τ. However, a learner's ability θ in relation to a goal q that is not actively pursued by that learner at time interval τ is valued -1 (i.e. $\theta_{q\tau} = -1$). Figure 4.5 contains an example of such an ability matrix. This example shows a learner's ability θ in relation to three goals in goal set Q at three different time intervals τ. The second goal in the example is not actively pursued by the learner at all time intervals τ and is therefore valued -1.

4.3 Assumptions and restrictions

Eagle Eye assumes, in line with Student Modeling [45, 2], that ability θ_q increases monotonically over time. Furthermore, Eagle Eye assumes that, in line with Item Response Theory, each

$$\begin{bmatrix} 0 & -1 & 0.3 \\ 0.1 & -1 & 0.4 \\ 0.2 & -1 & 0.4 \end{bmatrix}$$

Figure 4.5 Ability Matrix
Example of the output of Eagle Eye. The matrix describes the progress over three intervals (rows) for three goals (columns).

learning task can have a unique difficulty value (which is constant) and learners can have a unique ability value.

Eagle Eye is the progress measure proposed to answer this thesis' research question. In the next chapter it is described how Eagle Eye is applied to the PAL use case.

Chapter 5

Method

This chapter firstly goes into how Eagle Eye has been applied within the PAL use case. Secondly, it is described (i) how and on the basis of which data Eagle Eye has been trained and tested and (ii) how two test scenarios have been generated. Thirdly, this chapter sets out how, on the basis of those two test scenarios, semi-structured interviews with health-care professionals have been utilized in order to validate the applied version of Eagle Eye within the PAL system. Finally, the chapter describes how Eagle Eye is compared with PAL's current progress measure (CPM).

5.1 Application of Eagle Eye in the PAL use case

Eagle Eye is applied to the PAL use case by application of the statistical programming language R. In this implementation, Eagle Eye contains two main functions. The first function is *getKnowledgeState*, which calculates a specific child's knowledge state at a specific moment. Such knowledge state consists of one ability value for each active goal. The second function is *getProgress*, which calculates progress over a specified time period for a specific child. In order to calculate progress, *getProgress* invokes *getKnowledgeState* for each interval within the specified time period. *getProgress* merges all results from *getKnowledgeState* in one data frame. Figure 5.1 illustrates how the results of *getKnowledgeState* become the final result of *getProgress*. The data frame that results from *getProgress* is almost identical to the ability matrix as described in Section 4.2.4 and is shown in Figure 4.5. The two main differences between the ability matrix 4.5 and the data frame are the following:

- **Extra column:** the data frame contains one extra column to specify the exact interval that the row refers to.
- **Inactive goals:** goals that are not active at a certain interval contain value -1 in the ability matrix, but in the data frame inactive goals contain value NA. NA is a special value within R that refers to Not Available.

getKnowledgeState calculates a child's ability for each active goal at a specific moment. Such ability is calculated by dividing the total amount of difficulty for a goal by the difficulty that is attained at a specific moment. The code of *getKnowledgeState* corresponds with Equation 4.2 and 4.1. *getKnowledgeState* only takes quiz questions into account.

Furthermore, PAL utilizes the concept of difficulty level, which is a number set by an expert to indicate the difficulty of a learning task (see Section 7.2 for a discussion of PAL's difficulty parameter). Eagle Eye utilizes PAL's difficulty to set a learning task's difficulty parameter.

Goal	Ability
1	0
2	NA
3	0.3

Interval	Goal 1	Goal 2	Goal 3
1	0	NA	0.3
2	0.1	NA	0.4
3	0.2	NA	0.4

Goal	Ability
1	0.1
2	NA
3	0.4

Goal	Ability
1	0.2
2	NA
3	0.4

Figure 5.1 Progress measure data structure
The result of *getProgress* (data frame on the left) results from merging all results from *getKnowledgeState* in one data frame (three data frames on the right).

5.2 Eagle Eye trained and tested & scenario construction

Before Eagle Eye can be trained and tested with the data of the PAL use case, the different data structures as described in Section 3.3 are converted (wrangled) into a usable structure. In this section firstly the wrangling process is considered, after that it is set out how the dataset is created and finally how Eagle Eye is trained and tested within the PAL use case.

5.2.1 Data wrangling

The different sources of trace data as described in Section 3.3 have different data structures and may contain superfluous data, therefore the data is molded (wrangled) in a uniform structure. The result of this process is a dataset that can be queried and utilized. The data wrangling is executed with R. The four different sources from the PAL use-case are each converted to one uniform format. For each source a specific procedure (R script) is created to enable such conversion. The main steps of each script are the following:

1. Read all data into an R data frame.
2. Convert the structure into a data table.
3. Identify variables that can be used to map the data table with other data tables.
4. Enrich the data table with variables from other data tables if available.

For purposes of this research, step 3 is the most interesting as in this step it is determined which variables can be used to combine the sources. Table 3.1 shows what variables are available in which dataset. Based on that overview three new data frames are created that can be easily queried and utilized, namely AGT Ontology, AGT Instances and Quiz Data. What follows is an overview of what data resides in which data frame. See Figure 5.2 for a specific overview of the resulting data frames and their sources.

- **AGT Ontology**: A data table that contains an overview of all achievements, goals and tasks. Every row contains:
  1. either an achievement, goal or task entity,
  2. if applicable, the achievement of which the entity is part,
  3. if applicable, the goal of which the entity is part, and
  4. the type of entity (e.g. Achievement, LearningGoal, SortingGameTask, Videotask)
- **AGT Instances**: A data table that contains an overview of all instances of achievements, goals and tasks for each child in the Tuple Data. Every row contains:
  1. an instance of an Achievement, a LearningGoal or a LearningTask,
  2. a type indicator stating if the instance refers to an Achievement, a LearningGoal or a LearningTask,
  3. an indication of the exact type, which is equal to the entity names from AGT Ontology,
  4. identifier to relate the instance to the relevant child, and
  5. a time stamp referring to the time at which the instance is added to the data.
- **Quiz Data**: A data table in which every row describes a specific child's answer to a quiz question. The following columns are part of the data table:

1. the quiz question (including identifier if available),
2. which experiment the quiz question is part of, including country (either The Netherlands or Italy),
3. identifier to relate the instance to the relevant child,
4. response to the question (either Correct, Incorrect, Unanswered),
5. whom the question is asked by (either Child or Robot), and
6. timestamp of both the time that the child has received the question and the time that the child has answered the question (the latter only in case the child did answer the question).

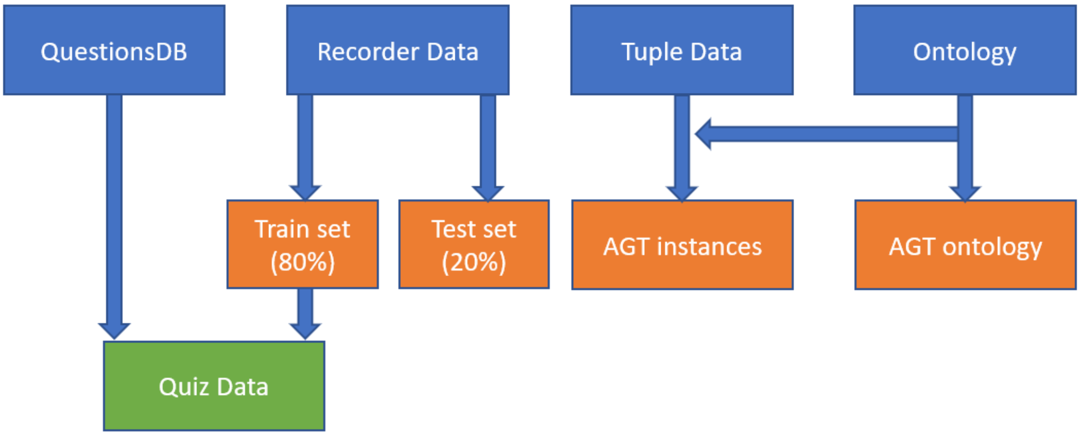


Figure 5.2 Data wrangling process
Illustration of how the different data structures from the PAL use-case are wrangled into different files. The blue boxes represent data collections as available from the PAL use-case. The orange and green boxes represent data tables that result from the wrangling process.

5.2.2 Dataset

As described in Section 3.3, each experiment with PAL contains different sets of goals, learning tasks and achievements. The data of year two is used for this research because at the moment of execution of this research only the data of year two was fully available. The data is divided into two sets: a training dataset and a test dataset. Because Eagle Eye does not contain any hyperparameters (parameters that should be set before training commences), a validation dataset is not used. The data of 80% of the children (participants) belongs to the training set, the data of the other 20% forms the test set. It is randomly chosen if a child's data belongs to the training set or to the test set. In order to determine if Eagle Eye performs similarly in relation to different data sets, Eagle Eye is trained and tested on another dataset than the PAL dataset as well: the ASSISTments 2009-2010 skill builder data set [1]. The results of training and testing in relation to both the PAL dataset and the ASSISTments dataset can subsequently be compared. The ASSISTments dataset contains the performance data of an online learning platform that offers learners different learning problems in order to obtain skills. Every row in the dataset describes a learner's behavior for a specific learning problem [19]. Furthermore, the dataset is also used in other research as described in related literature, such as [48, 47]. In the same fashion as the PAL dataset, the ASSISTments dataset is also divided in a training dataset that contains the data of 80% of the participants and a test dataset that contains the remaining data.

5.2.3 Training: average attempt rate calculation

In relation to the PAL use case, the average attempt rate α_i for a quiz question i is calculated as follows. All children's attempts to solve a quiz question that resulted in unanswered are treated as incorrect, as unanswered could imply that a child does not know the answer. Why a child did not answer a quiz question can however not be validated as the PAL dataset does not explain why a child did not answer a quiz question. In order to calculate the average attempt rate α_i, as explained in Section 4.2.2, all attempts by children that answered quiz question i correctly at a certain moment are selected from the training dataset (data of children that never answered quiz question i correctly is ignored). α_i is equal to the average number of attempts that those children needed to solve question i correctly. If a quiz question i is not answered correctly by any child in the training dataset, α_i is equal to the average α of those questions that were answered correctly. For the ASSISTments dataset, the same approach is utilized to calculate the average attempt rate α_i for a question i (in this dataset, a question is called a problem).

5.2.4 Testing: average attempt rate

In order to evaluate if the average attempt rates, as learned from the training dataset, are an accurate indicator for the number of attempts needed by a child to correctly answer a question, the average attempt rates are tested on the test dataset as follows. For the PAL dataset, the results of training on the PAL use case are utilized. For the ASSISTments dataset, the results of training on the ASSISTments dataset are utilized. All attempts by children (participants) that answered a quiz question (learning problem) correctly at a certain moment are selected (i.e. attempts that never led to a correct answer are ignored). Then a specific child's attempt rate regarding a specific question is compared with that question's average attempt rate as obtained from the training dataset. Based on those results, different evaluation metrics are calculated.

5.2.5 Testing: scenario construction

A scenario describes exactly one child's progress within the PAL system based on Eagle Eye's results. For this research, two scenarios are constructed based on the test set. As not all children in the test dataset used PAL a lot, those two children that have generated the most data in the test set are utilized for scenario construction. The progress of a child is obtained by calculating the ability of a child at the start of using the PAL system and for every 24-hour interval after that starting point. The calculation of progress is performed by invoking the function *getProgress* as discussed in Section 5.1. The result that serves as input for each scenario is an ability matrix as described in Section 4.2.4. The ability matrix that results from the calculation is then visualized with a line chart.

5.3 Validation: semi-structured interviews

Semi-structured interviews have been utilized to validate if the results of Eagle Eye (i) are effective for the purpose of evaluating a learner's progress and (ii) can be beneficial for, if necessary, choosing adaptations to a learner's learning path. This section firstly describes how (i) the selection of participants has been carried out, (ii) the instrumentation has been selected and utilized and (iii) the procedure that has been followed for the interviews that have been conducted.

5.3.1 Participants

Three health-care professionals have been selected for the purpose of carrying out semi-structured interviews. The three health-care professionals are all child diabetes nurses located in the Netherlands. The participants all have experience with the PAL system and thus all have a clear understanding of the way that the PAL system utilizes learning tasks, goals and achievements in order to educate children with diabetes.

5.3.2 Instrumentation

The selected participants were interviewed based on a semi-structured interview in the Dutch language. The interviews consist of both closed and open questions. The first part entails questions aimed at tracing what factors of a progress measure the participants find valuable. The goal behind the first part is to let a participant think about such factors and to qualify what factors a participant will probably analyze in the second part of the interview. The second part of the interviews consists of an explanation of Eagle Eye, a test of the explanation (called case 1) and two cases of Eagle Eye applied to the PAL system (called case 2 and 3). All interviews have been conducted on the basis of a questionnaire (a translation of the questionnaire is attached as appendix 1). All questions listed in the questionnaire have been discussed and optimized beforehand based on conversations with the company supervisors. The responses to the closed questions have been measured with a 5-point Likert scale.

5.3.3 Data collection

The semi-structured interviews have the form of a paper-and-pencil test. Each participant receives the same questions. Therefore, the interview is of high structure and high fidelity. To ensure an audit trail, all interviews are recorded, and the written responses are digitized and archived (the written responses are attached in Appendix 2). Furthermore, member check can be ensured as the names and contact information of the participants are known by the author and company supervisors.

Reliability and validity

Due to the small number of participants, this research cannot make any claims with regard to reliability and validity of the interview's results. In order to replicate the interview, the interviewer needs a clear and thorough understanding of both the PAL system and workings of Eagle Eye. The design of the interview is chosen based on a few factors:

- **Size of participants pool:** in total 6-8 health-care professionals divided over the Netherlands and Italy are working with the PAL system. Because of the small pool of participants and time constraints, the form of a qualitative research has been chosen.
- **Off-line implementation:** Eagle Eye is implemented based on data that is available from the PAL experiment of year two. Because the last version of PAL uses different goals and learning tasks than the version of year two, the tailored version of Eagle Eye cannot be directly used for the current version of PAL. Therefore, the scenarios are created in such a way that they are independent of PAL's current version in order to allow replication of the interviews in the future if necessary.

5.3.4 Procedures

The participants have been contacted by email with the request to participate in a 30 minute semi-structured interview.

The process of the interview is as follows:

1. the interviewee is informed about the goals and context of this research,
2. consent to record the interview is asked,
3. a questionnaire is provided to the interviewee and the interviewer explains the general setup of the interview, and
4. the interviewee starts to fill-in the questionnaire. During the interview, the interviewer asks for elaboration on the answers provided to the questionnaire if needed to elicit information about the different subjects that are part of the interview.

The resulting tapes and handwritten filled-in questionnaires are utilized as input for analysis.

5.4 Qualitative comparison between PAL's current progress measure (CPM) and Eagle Eye

PAL's current progress measure (CPM) and Eagle Eye are qualitatively compared based on a list of features. Such list of features exists of a collection of those topics that health-care professionals have indicated to find valuable for evaluation of a learner's progress. Both progress measures are analyzed and compared for each individual feature.

Chapter 6

Results

In this chapter, the results of applying the method (as set out in chapter 4) are described. Firstly, the results of training and testing Eagle Eye on both the PAL dataset and the ASSISTments dataset are set out. Secondly, the two example scenarios from the PAL use-case are described, which are also used to validate Eagle Eye. Thirdly, the results of the validation are discussed. Finally, PAL's current progress measure and Eagle Eye are qualitatively compared.

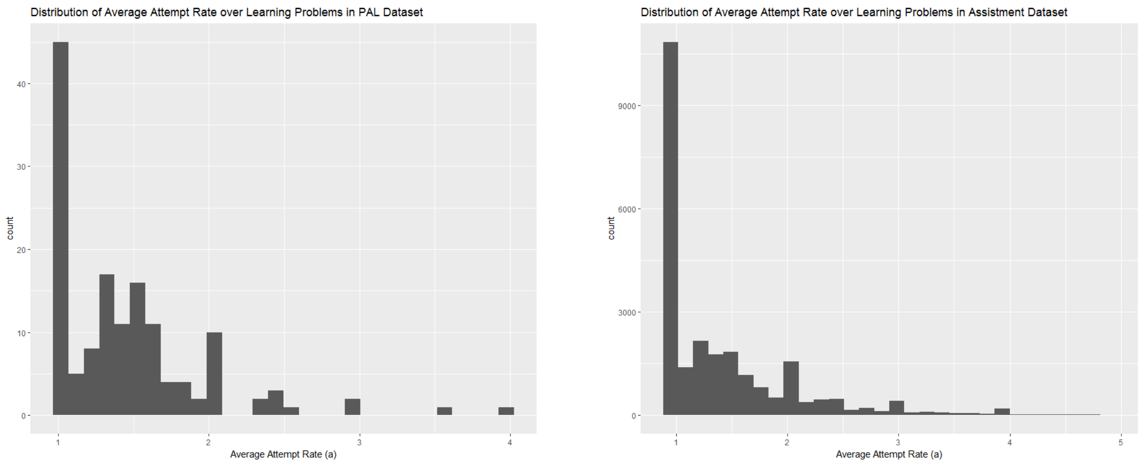
6.1 Eagle Eye trained and tested & scenario construction

6.1.1 Dataset

For training and testing, the dataset of year two is utilized (as explained in Section 5.2). This dataset contains the data of 41 children. The dataset is divided in two sets, the data of 32 randomly chosen children (80%) belongs to the training set and the data of the remaining 9 children (20%) makes up the test set.

6.1.2 Training: average attempt rate calculation

The PAL dataset contains 143 different quiz questions. Three questions were not answered correctly by any child in the training set. Therefore, the average attempt rate α for those three questions is equal to the average α of the remaining 140 questions (which is 1.31). The distribution of average attempt rate α values for the remaining 140 questions are shown in a histogram, see Figure 6.1. The ASSISTments dataset contained 25,632 different learning problems. 958 learning problems were not answered correctly by any participant. The average attempt rate for those 958 learning problems is therefore equal to the other 20,088 learning problem's average attempt rate, which is 1.65. The distribution of average attempt rate α for the other 20,088 questions is shown in Figure 6.1b (in this Figure, average attempt rates above 5 are identified as outliers and therefore neglected (0.2% of total questions)).



(a) PAL training dataset

(b) ASSISTments training dataset

Figure 6.1 Distribution of average attempt rate α

Table 6.1 Evaluation metrics for Eagle Eye on the PAL dataset and the ASSISTments dataset.

Source	**Dataset**	**# Records**	**# Learners**	**# Unique problems**	**RMSE**	**MAE**	**Mean(α)**	**Sd(α)**
PAL Year two	Training dataset	1,164	31	140	0.82	0.56	1.45	0.50
	Test dataset	266	8	112	0.83	0.64	n.a.	n.a.
	Full dataset	1,430	39	143	n.a.	n.a.	n.a.	n.a.
ASSISTments Dataset	Training dataset	302,517	3,364	25,632	11.34	0.87	1.65	2.75
	Test dataset	89,842	842	20,088	14.06	0.92	n.a.	n.a.
	Full dataset	392,359	4,206	26,590	n.a.	n.a.	n.a.	n.a.

6.1.3 Testing: average attempt rate

The evaluation metrics of testing Eagle Eye on both the test dataset and the train dataset are shown in Table 6.1.

Selection of children

The PAL test set contains data of eight children and in total 53,812 datapoints. See 6.2 for an overview of the distribution of datapoints over the children. As discussed in Section 3.3 a datapoint can contain different types of information which may not be related to progress.

The active *learning goals* of both the children that have been selected for scenario creation are stated in stated in the legend of Figure 6.2 (child 1) and Figure 6.3 (child 2). Within the PAL

Table 6.2 Datapoints per child in the test set

Child:	#Datapoints:	% of total
1	16,364	30.41%
2	13,148	24.43%
3	9,389	17.45%
4	5,786	10.75%
5	5,128	9.53%
6	3,546	6.59%
7	329	0.61%
8	122	0.23%
Sum:	**53,812**	**100%**

system it is possible to activate or deactivate *learning goals*, but as can be concluded from the data such did not happen in relation to those two children.

Child 1

Child 1 had activated 21 of the 38 goals available in the system. Child 1's progress is visualized in Figure 6.2. From this visualization it can be concluded that child 1 started using the system at day 19. Probably the system was already configured before the child actually started.

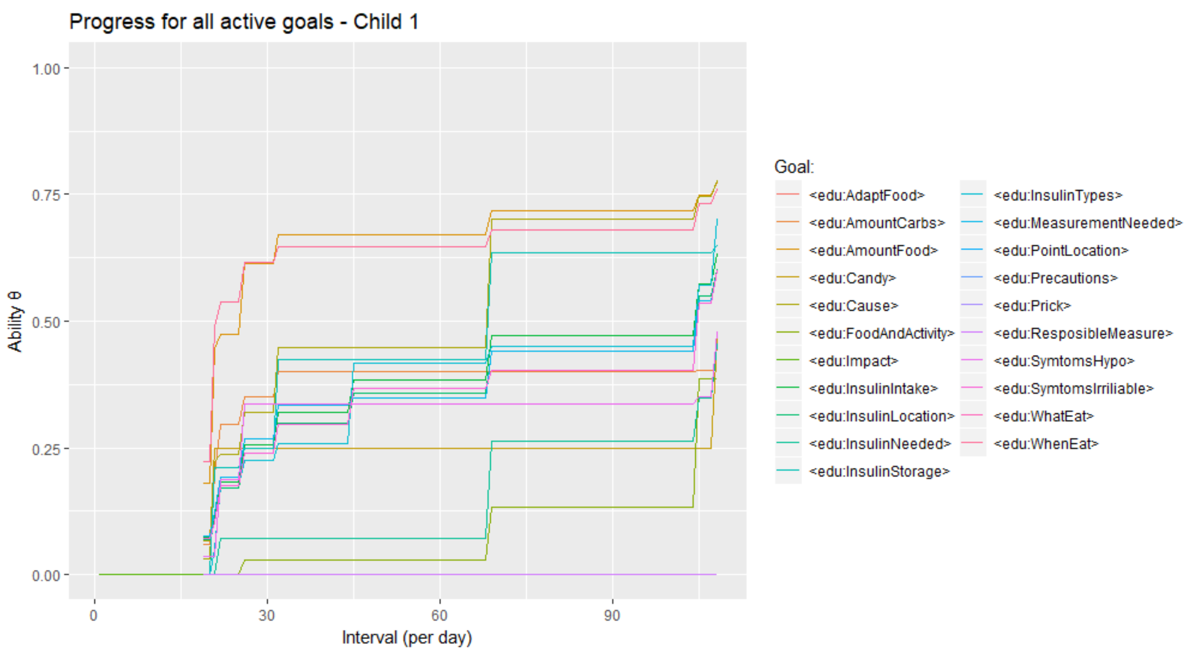


Figure 6.2 Ability progress for active goals (child 1)

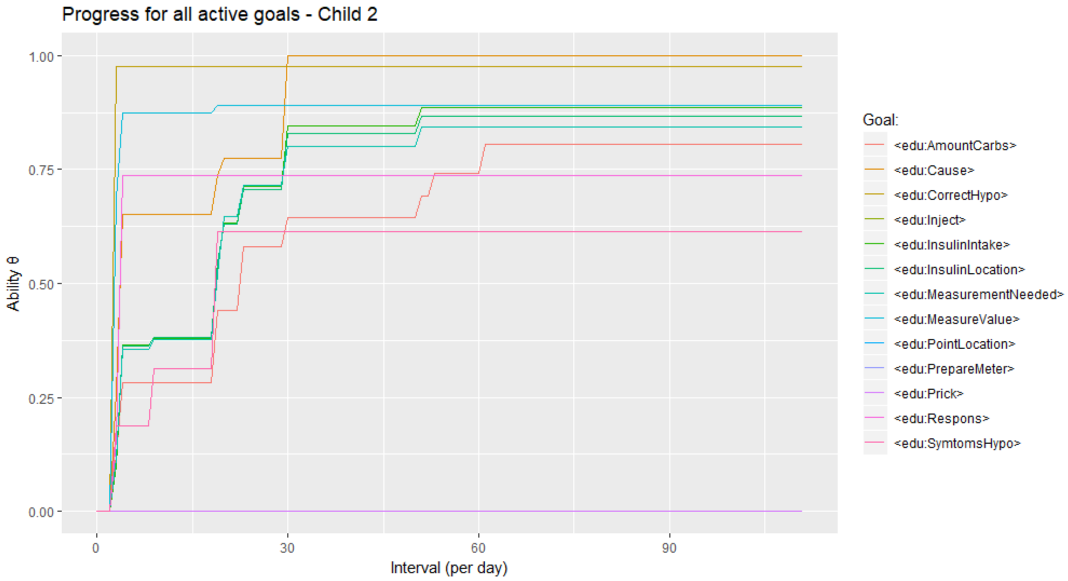


Figure 6.3 Ability Progress for active goals (child 2)

Child 2

Of the 38 goals available in the system, child 2 had 15 active goals. Child 2's progress is visualized in Figure 6.3. The black line represents the mean progress over all active goals.

6.2 Validation: semi-structured interviews

In this section the results of the interviews are summarized and discussed. The analysis follows the structure of the questionnaire (which is attached as Appendix 1). The transcriptions of the semi-structured interviews are attached as Appendix 2.

6.2.1 Part 1

The first part of the semi-structured interview focuses on the participants' experience with PAL and is aimed at tracing what factors of a progress measure the participants find valuable. The participants' experience with PAL ranges from average (two participants) to a lot (one participant). Participants have face-to-face contact with the child two to three times during a PAL experiment. Besides face-to-face contact, one participant mentioned that she at times also has telephone contact with children in between the face-to-face meetings. Participants indicated unanimously that they would like to assess the progress of a child over the period of one month. With regard to the frequency, two participants prefer a once a month assessment and one participant prefers a weekly assessment. One participant indicated to prefer a monthly email update regarding a child's progress. The participants reported that the following factors regarding a progress measure are important:

- **Learning progress:** all participants indicated that it would be valuable to know which goals and achievements have been obtained by a child.

- **System usage frequency:** one participant indicated that, in order to make a better evaluation of the system's contribution to a child's learning progress, it would be valuable to be informed about the system's usage frequency.

- **Motivation:** two participants indicated that it would help to see how motivated a child is regarding usage of the PAL system.

- **Glucose measurements:** two participants indicated that it would be valuable to be informed about measurements regarding blood glucose and glycated hemoglobin, as both measurements express a child's competence in handling diabetes.

- **Learning tasks:** one participant wishes to know what types of learning tasks a child prefers, another participant would like to know what learning tasks are challenging for a child and a third participant prefers to be informed about learning tasks that take place outside of the system (called life events).

- **Technical issues:** one participant wishes to be updated on technical problems, e.g. that the tablet did not work or that the server was unavailable. Such information would enable health-care professionals, in case a child's progress is plateauing, to determine if such plateauing could be caused by technical issues.

6.2.2 Part 2

The second part of the semi-structured interviews focuses on results produced by Eagle Eye based on the data of the two selected children as described in Section 6.1.3. Part 2 consists of three different cases.

Case 1

Case 1 gives the participant information on the theory behind Eagle Eye. Based on information in the questionnaire that describes (i) how Eagle Eye is applied to PAL and (ii) what information results from Eagle Eye if just one learning goal is taken into account, all participants reported more or less the following:

- A child's progress can be clearly obtained from the information provided in the questionnaire and it is clear how Eagle Eye calculates the progress in this case.

- A child's progress can be utilized to estimate what a child needs to optimally learn from PAL and it is clear if a child's goals need to be adjusted or if a child needs something else outside of PAL.

One participant mentioned as a side-note that the above is true for case 1, but that it is not clear what it would look like if Eagle Eye would be integrated within the PAL system.

Case 2

Case 2 shows child 1's active goals as discussed in Section 6.1.3 and it shows a table with child 1's ability for each goal one month after child 1 has started using PAL. Furthermore, a graph reminiscent of 6.2 is shown, reflecting child 1's ability progress over the first 31 days from the date that the child has started using PAL. One participant indicated that numbers are preferable over graphs and therefore this participant mainly made use of the information from the table to fill in the statements. The other two participants focused on both the table and the graph. One participant indicated that in this case child 1 needs more stimulation to keep child 1 motivated to keep using the system. Another participant evaluated that child 1 was motivated at the beginning, but later in the process child 1 lost its motivation. Therefore child 1 should be actively approached to be encouraged to use the PAL system more. All three participants agreed that child 1's progress can be clearly obtained from the information provided in the questionnaire and that it is clear how Eagle Eye has calculated the progress. Furthermore, all three participants state that the information provided can be used to estimate what child 1 would need to optimally learn from PAL and to determine if child 1's goals would need to be adjusted or if child 1 would need something else from outside of PAL.

Case 3

Case 3 shows child 2's progress as discussed in Section 6.1.3 in the same fashion as child 1's progress in case 2, except that in this case progress is shown over two months instead of 31 days. Based on this case, two participants stated that contact on a regular basis would improve motivation of child 2 and that it would result in a higher progress. Furthermore, one participant noted that not all learning tasks have been executed by child 2 and that it would be valuable to ask child 2 why certain goals have not yet been achieved. Furthermore, this participant would use the information provided in case 3 to discuss with child 2 if one or more goals should be added to the goal selection. All participants agreed, even stronger than in relation to case 2, that child 2's progress can be clearly obtained from the information provided in the questionnaire and that it is clear how Eagle Eye has calculated the progress. Furthermore, all participants state that the information provided can be used to estimate what child 2 would need to optimally learn from PAL and to determine if child 2's goals would need to be adjusted or if child 2 would need something else from outside of PAL.

6.3 Qualitative comparison between PAL's current progress measure (CPM) and Eagle Eye

As mentioned above, the interviewed health-care professionals have indicated that it is important to receive information on the following topics in order to be able to evaluate a learner's progress: learning progress, system usage frequency, motivation, glucose measurements, learning tasks and technical issues. In this section, a qualitative comparison between PAL's current progress measure (CPM) and Eagle Eye is made on the basis of the topics identified above. See Table 6.3 for a brief overview of this comparison.

6.3.1 Learning Progress

CPM reports the current learning progress on three levels: for every active goal, achievement and learning task. Eagle Eye only reports learning progress for every active goal (and does so over time). Achievements however are not included. Furthermore, the exact learning tasks that have led to progress cannot be derived from Eagle Eye's results.

6.3.2 System usage frequency

For this comparison it is assumed that system usage within PAL implies that a child utilizes the system to attempt to solve learning tasks. CPM does not show any information related to system usage frequency. However, system usage frequency can be derived from Eagle Eye's results, as with every child's attempt (successful or unsuccessful) to solve a learning task Eagle Eye increases a child's progress.

6.3.3 Motivation

Currently, the PAL system does not explicitly inquire children about their feelings regarding the PAL system. Therefore, it is not possible to directly make use of data regarding a child's motivation as it is not available. However, system usage frequency can be utilized to detect a learner's disengagement, which imply that a child lost its motivation [13]. I.e. a motivated child will use the system more frequently than a non-motivated child. This assumption is utilized to compare both progress measures regarding the topic of motivation. CPM shows a child's current progress percentage regarding every active goal, achievement and learning task. An average low progress percentage could indicate a low value for motivation and an average high percentage could indicate the opposite. However, this theory is not solid as a low progress percentage could also be caused by the fact that a child has just started using the system. On the other hand, a high average progress percentage does not necessarily indicate a high motivation as it is possible that the child has achieved all goals a long time ago. Contrarily, Eagle Eye shows a child's progress

Table 6.3 Overview of comparison between CPM and Eagle for output provided on each topic

Topic	**CPM**	**Eagle Eye**
Learning Progress	Goals, achievements and learning tasks.	Goals
System usage frequency	No	Yes
Motivation	Probably not	Probably yes
Glucose measurements	No	No
Learning Tasks	Learning Task Type preferences	No
Technical Issues	No	No

over time. System usage frequency is incorporated in such progress and therefore, health-care professionals can derive a child's motivation regarding usage of the PAL system at a specific moment in time from a child's progress.

6.3.4 Glucose measurements

However, the PAL system only sporadically takes into account such measurements. Therefore, this information is currently not incorporated in both CPM and Eagle Eye.

6.3.5 Learning tasks

CPM reports progress for each individual learning task. Because CPM only reports if a learning task is completed (100%) or not (0%), health-care professionals cannot derive how often a child has attempted a learning task and thus if that learning task is challenging for that child. Eagle Eye does also not report on particular challenging learning tasks, but it does report on challenging goals. In case a goal is challenging for a child, a child's progress reflects that by small, but frequent increases in a child's progress. As CPM reports on each individual learning task, health-care professionals could analyze if patterns exist regarding the type of learning tasks that are completed and the type that are not completed. Although this is possible, it is a time-consuming and meticulous process. Eagle Eye reports progress on the level of goals. As Eagle Eye does not report on the level of learning tasks, health-care professionals cannot derive which types of learning tasks a child prefers. Learning tasks that take place outside the system are not considered by both CPM and Eagle Eye.

6.3.6 Technical issues

Both CPM and Eagle Eye do not report on technical issues.

Chapter 7

Discussion and Conclusion

This chapter starts with a discussion of this thesis' research findings, followed by its limitations and opportunities for further research. The chapter closes with a general conclusion.

7.1 Discussion and interpretation

This section follows the structure of the previous chapter. This section starts with a discussion of Eagle Eye's accuracy, based on Eagle Eye's performance on the PAL and ASSISTments datasets. Secondly, an interpretation of the outcomes of the semi-structured interviews is considered. Thirdly, the comparison between the current progress measure and Eagle Eye is interpreted. And finally, the improvements that lay the basis of Eagle Eye are discussed.

Model accuracy

Eagle Eye has been both trained and tested on the PAL year two dataset and the ASSISTments dataset. The PAL training dataset contained the data of 31 learners that solved 1,164 questions in total (143 unique questions). The model that was trained on the PAL training dataset could predict the attempt rate needed for the 8 learners that solved 266 questions with a mean absolute error of 0.64. In other words, on average the model prediction differed 0.64 from the actual number of attempts that learners needed to solve a learning task correctly. See Table 6.1. The ASSISTments training dataset on the other hand contained the data of 3,364 learners who together solved 302,517 questions (26,590 unique questions). The model that was trained on the ASSISTments training dataset performed with a mean absolute error of 0.92 on the ASSISTments test dataset. In conclusion, looking at the mean absolute error, Eagle Eye performed better on the PAL testing dataset than on the ASSISTments testing dataset. The difference could be explained in one of two ways:

- **Spread of α:** the ASSISTments training dataset contained more records (302.517) than the PAL training dataset (1.430). In case the spread of average attempt rates (α) would be equivalent in both sets, then one could expect a lower mean absolute error for the ASSISTments testing dataset because it is significantly larger than the PAL dataset. However, the spread of the average attempt rate (α) is lower in the PAL training dataset (standard deviation of 0.50) than in the ASSISTments training dataset (standard deviation of 2.75). This bigger spread could explain the higher mean absolute error on the ASSISTments testing dataset.

- **Availability of questions in the training dataset:** in the ASSISTments training dataset, 958 unique questions (3.6%) were not answered correctly once and in the PAL training dataset 3 unique questions (2.1%) were not answered correctly once. Thus, no data was available for those questions. Therefore, the average attempt rate for those questions is equal to the mean average attempt rate of the questions that did contain data in the training sets. However, given the spread of α, such prediction can be far off the real value. The fact that spread and the percentage of unavailable questions is higher in the ASSISTments training dataset than in the PAL training dataset could explain the higher mean absolute error on the ASSISTments testing dataset.

In conclusion, Eagle Eye's performance is highly dependent on the spread of the average attempt rate in a training set and the number of records per unique question. Therefore its performance in relation to the two datasets is not equal.

The author did not anticipate that (i) the spread of questions over different datasets differs to such extents and (ii) that the number of unsolved unique questions in the training set was so high. Therefore, it would be valuable for future research to examine different strategies that predict average attempt rates of questions that did not occur in the training dataset.

Validation: semi-structured interviews

Semi-structured interviews with health-care professionals have been utilized to validate if Eagle Eye's results are effective for the purpose of evaluating a learner's progress. For that validation the trace data of two children from the PAL testing dataset has been used. The health-care professionals all stated that they understand Eagle Eye's calculation and that Eagle Eye's results can be utilized to evaluate a learner's progress and to adapt a learner's goals if needed. Thus, based on this validation it seems likely that the results produced by Eagle Eye, as applied to the PAL use case, are (i) understandable for health-care professionals and (ii) can support health-care professionals to evaluate if a child's selection of active goals needs to be changed.

Comparison between PAL's current progress measure and Eagle Eye

From the qualitative comparative analysis in Section 6.3 it can be learned that PAL's current progress measure (CPM) scores high on reporting progress in relation to all levels (goals, achievements and learning tasks), while Eagle Eye only reports progress regarding goals.

Furthermore, CPM could give insight into what learning task types are preferred by a child, albeit with a large amount of meticulous manual labor. On the other hand, CPM does not report on system usage frequency while Eagle Eye does. System usage frequency itself contains a valuable insight for health-care professionals and secondly, on the basis of system usage frequency a child's engagement (and motivation) regarding the PAL system can be derived. According to the Flow theory [16], a learner's motivation towards learning is an important condition to achieve learning goals. Eagle Eye, contrary to CPM, provides insight in motivation. Therefore health-care professionals can evaluate a child's motivation and, in case the motivation is low, adapt the child's goals with the aim of improving that child's motivation. Improved motivation will positively influence children's system usage frequency which will ultimately have a positive effect on children's progress, and thus on the achievement of learning goals. As the achievement of learning goals leads to the improvement of self-management skills, the author has a strong impression that in comparison to CPM, Eagle Eye will cause the PAL system to lead to a bigger improvement of children's self-management skills. However, an even better progress measure would combine the strong features of CPM (progress regarding all levels) with the strong features of Eagle Eye (progress over time and system usage frequency).

Evaluation of Eagle Eye's improvements

In Section 4.1 the two identified potential improvements that formed the foundation of Eagle Eye were discussed. The first improvement, 'Learning tasks are unequal', states that progress that can be obtained by successfully solving a learning task should be proportional to a learning task's difficulty. From this research results it cannot be concluded that those parts of Eagle Eye related to the first improvement are (partly) responsible for Eagle Eye's positive evaluation. The second improvement, 'All learning activity leads to progress', states that unsuccessful attempts should be taken into account in progress calculation. This improvement is responsible for the fact that Eagle Eye, unlike CPM, reports on system usage frequency. As argued above, health-care professionals can utilize system usage frequency to derive motivation. Therefore, only the second improvement can be tied to Eagle Eye's positive evaluation.

7.2 Limitations and future work

The following limitations need to be recognized in regard to this study.

Environment

Eagle Eye has not been tested within a live environment of the PAL system. At the start of this research the intention was to include Eagle Eye as part of that version of the PAL system that was utilized for year 4's experiment. However, due to the short time available before the deadline for year 4's version of the PAL system, it was decided to create an off-line implementation using data from a previous experiment. This could be a limitation as health-care professionals have been able to reflect on the progress of a child, but they were unable to experience the effects of their decisions on an ongoing progress in a live PAL environment.

Computer interpretability

Eagle Eye has not been tested for the computer interpretability design constraint. Due to lack of time, the author has decided not to include this in the scope of this thesis. For future research, it would be valuable to (i) test Eagle Eye's computer interpretability and (ii) build a classifier upon Eagle Eye that is able to automatically analyze Eagle Eye's results and detect certain learner characteristics such as 'motivated' versus 'non-motivated'. This next step would help health-care professionals to interpret Eagle Eye's results with less effort.

Number of participants

Only three participants contributed to the study. On the basis of the results from those three participants, an indication of the human interpretability of Eagle Eye has been obtained. For future research, it would be of value to collect results from more participants (on the basis of semi-structured interviews, see also Appendix 2) in order to improve the robustness of this research' results.

Other intelligent tutoring systems

In order to investigate if Eagle Eye is beneficial for learning experts that work with other intelligent tutoring systems, it would be valuable to apply Eagle Eye to other intelligent tutoring systems that (i) needs learning experts for the adaptation of goals and (ii) utilize a goal-framework equivalent to PAL's goal-framework.

Distribution of average attempt rate

The distribution of average attempt rate for both the PAL dataset and the ASSISTments dataset, as plotted in Figure 6.1, is skewed to the right. In other words, a big portion of the learning problems in those datasets is solved successfully at the first attempt. From Equation 4.3 it can be obtained that, in case a learner answers incorrectly, only learning problems that have an average attempt rate of 3 or higher result in a linear increase of attained difficulty points. See Figure 7.1 for an illustration. For further research it would be interesting to develop a more sensitive model that can also be applied in relation to learning problems with an average attempt rate below 3.

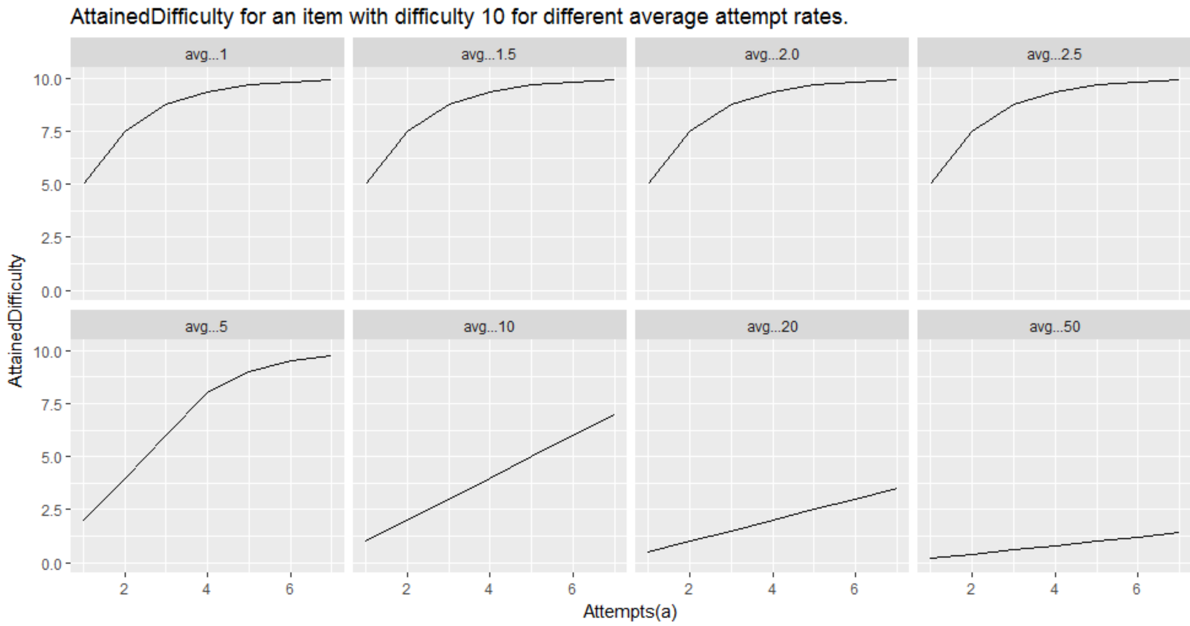


Figure 7.1 Graph of the function d_i for multiple values of alpha

PAL's difficulty level

For the execution of this research experiment, Eagle Eye uses the difficulty level of a PAL learning task as the difficulty parameter B_i. However, PAL's difficulty level does not always adhere to the exact properties as stated in Section 4.2.1. At the time of execution of the experiment, on the basis of various conversations, the author discovered that the ontological meaning of difficulty level in the PAL system is 'development level'. Although development level is closely related to difficulty level, it does not always imply difficulty level, as development level also relates to age (young children generally have a lower development level than older children). Therefore, a learning expert's decision to classify a PAL's learning task at a specific development level can be based on either (i) the difficulty of a learning task, or (ii) the children's age category for which a learning task is intended.

The following serves as an example of such classification based on the latter reason described above: a learning expert classifies a learning task i related to puberty at a high difficulty level as such learning task is intended for older children. However, in this case, the high difficulty level does not necessarily imply that learning task i actually is very difficult. Eagle Eye calculates progress proportional to the difficulty level, as it assumes that the difficulty level is proportional to the time needed to solve a learning task (as set out in Section 4.2.1). However, for learning tasks that are classified with a high difficulty level because of its high age category, the difficulty level is not per se proportional to the time needed to solve that learning task and therefore such a learning task does not adhere to the properties listed in Section 4.2.1. Thus, learning tasks that have been categorized with a high difficulty level because of the intended age category can be problematic for Eagle Eye's progress calculation.

In further research, the above could be taken into account in the following manners:

- The property ‘difficulty level’ could be split into two properties: age, which encodes the age category for which the learning task is intended, and difficulty, which encodes a learning task’s difficulty as defined in Section 4.2.1.
- Eagle Eye could ignore PAL’s difficulty levels and utilize a difficulty value based upon calculations. Such value could be based on historical performance data. For example, the average time needed by learners to solve a specific learning task, corrected for a learner’s age.

Subjectivity of difficulty

According to [14] learning task difficulty is non-objective. In experiments, researchers calculated a learning task’s difficulty based on Item Response Theory and compared the outcome with difficulty estimations of both students and teachers. In some experiments students’ estimations were closer to a learning task’s calculated difficulty than teachers’ estimations. Taking into account this subjectivity, it would be interesting to see how Eagle Eye would perform with difficulty values that are learned from data.

Binary classification

The version of Eagle Eye proposed in this thesis assumes that the outcome of an attempt is binary, namely ’correct’ or ’incorrect’. It would be interesting to see how other outcomes of an attempt, such as ’unanswered’ (which occurs within the PAL case), could be incorporated. Furthermore, it would be interesting to widen the binary scale to include more diversifications such as ’very wrong’ or ’almost correct’.

Achievements

Eagle Eye currently utilizes learning goals as main dimension of the ability matrix. As healthcare professionals indicated in the semi-structured interviews, information regarding which achievements a learner has fulfilled would be helpful to evaluate a learner’s progress. Therefore, it would be of value to research how PAL’s hierarchical achievements could be incorporated within Eagle Eye’s output structure.

Dynamic average attempt rate

If the training set is small, the average attempt rate could be inaccurate as Eagle Eye learns it from training data at only one moment in time and from that moment on regards the average attempt rate to be a constant. It would be interesting to see how Eagle Eye could calculate the average attempt rate dynamically. Such a dynamic calculation could result in a more accurate average attempt rate, especially in relation to a small training set, as it also takes into account newly obtained data for its calculation.

7.3 Conclusion

The main question of this research was: How should progress in relation to goal-driven educational activities, offered to learners on a digital device, be calculated on the basis of a learner's performance, knowledge, user experience and context data in such a way that the human expert ("health-care professional") can improve goal-setting? To answer this question, a progress measure called Eagle Eye has been proposed as set out in Chapter 4. Subsequently, Eagle Eye has been applied to the PAL use case, an intelligent tutoring system aimed to teach children with Diabetes type 1 self-management skills. As a form of validation, three health-care professionals have been interviewed about the results produced by Eagle Eye. All three health-care professionals stated that a child's progress can be clearly evaluated on the basis of Eagle Eye's output. Additionally, the three health-care professionals all stated that such output can be utilized to (i) estimate what a child will need to optimally learn from PAL, and (ii) determine if a child's goals need to be adjusted. Furthermore, based on the comparison between Eagle Eye and PAL's current progress measure, the author has a strong impression that Eagle Eye will cause the PAL system to lead to a bigger improvement of children's self-management skills, as Eagle Eye reports on system usage frequency, which can be utilized to derive a child's system engagement.

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Questionnaire

The aim of this questionnaire is to assess which factors of a progress measure are important within the PAL project.

QUESTIONAIRRE PROGRESS MEASURE PAL

Date (dd/mm/yyyy):

Name:

Function:

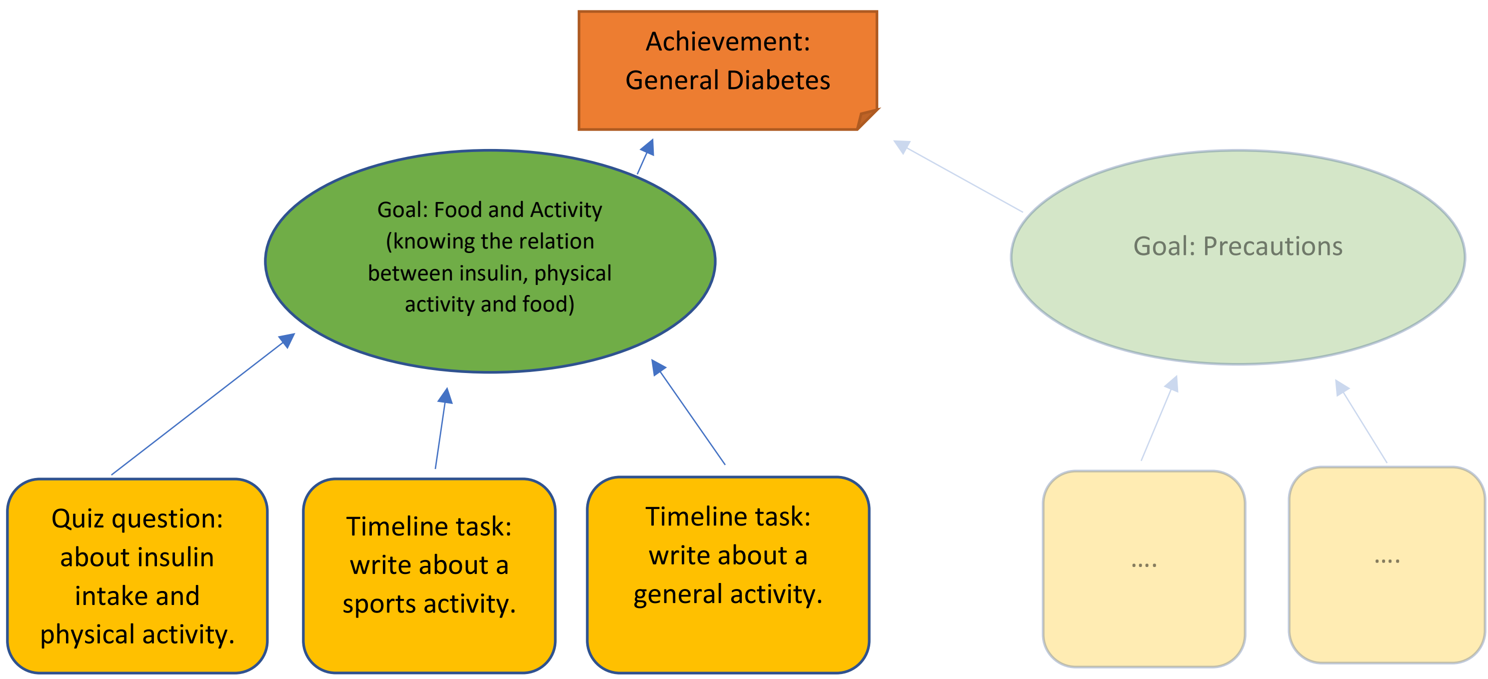
	Very little	A little	Somewhat	A lot	To a great extent.
Experience with PAL:	☐	☐	☐	☐	☐
How often do you have contact with a child that uses the PAL system?					

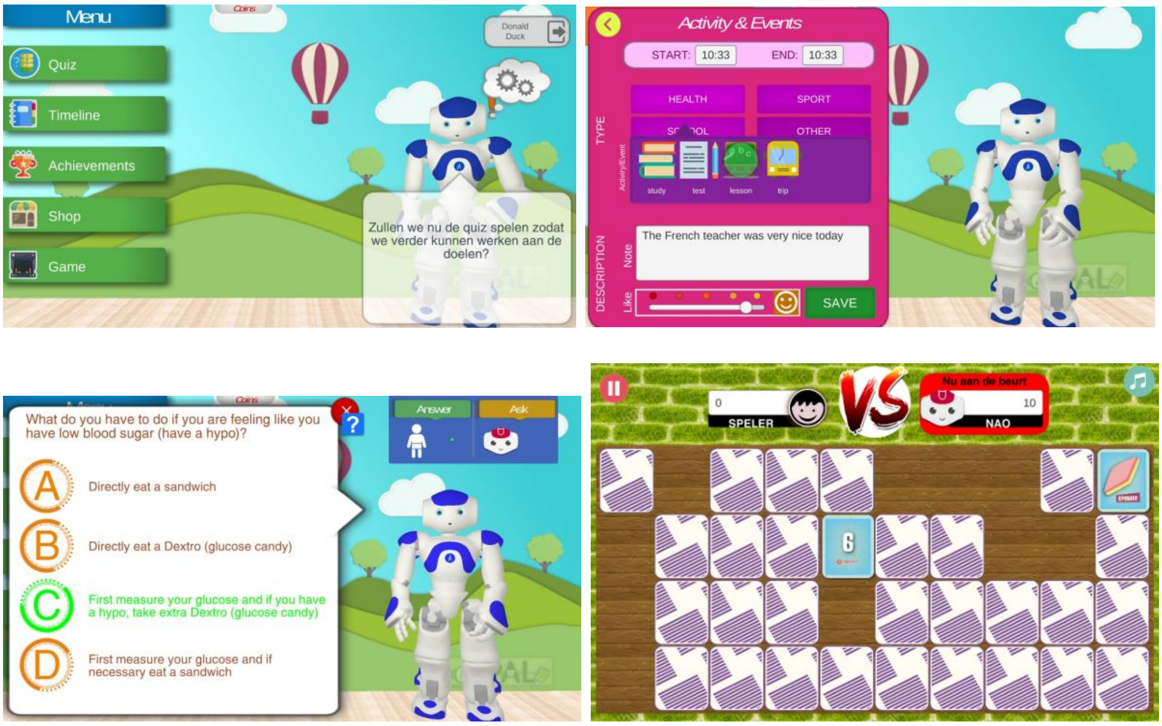
The PAL System

Education within PAL is goal-driven. A child can have one or more active goals.

A goal is achieved if all tasks that belong to a goal are successfully solved. An achievement can be achieved if a child completes a certain combination of goals.

Example: the goal **Food and Activity** is about the relation between insulin, physical activity and food. The goal is achieved if the following tasks are successfully completed: one quiz question about carbohydrates and two timeline tasks. In case a child a achieved **Food and Activity** and also the goal **Precautions**, then a child receives the Achievement **General Diabetes** (see illustration below).





The PAL app contains multiple types of learning tasks, such as quiz questions, timeline tasks and games. The pictures above provides a general impression of the PAL app.

Important factors of a progress measure.

If you could determine what information the PAL system would provide you with regarding progress of a child, (i.e. information that you could utilize to evaluate the progress of a child). What information would you like to see?

Please arrange the answers of the previous question by priority:

1. ………………………………………………………………………………
2. ………………………………………………………………………………
3. ………………………………………………………………………………
4. ………………………………………………………………………………
5. ………………………………………………………………………………
6. ………………………………………………………………………………
7. ………………………………………………………………………………
8. ………………………………………………………………………………

With what frequency would you like to analyze the progress of a child?

And over what time length would like to see such progress?

Explanation of the progress measure

- Progress is measured per goal and is expressed as a percentage.
- The percentage is determined by the number of tasks that have been completed for a goal.
- For a quiz question, it is a bit more advanced: each quiz question has an average attempt rate. The average attempt rate is the number of times that children on average need to answer a particular quiz question correctly. The average attempt rate is utilized to calculate the progress for a quiz question.

  An example:
  A quiz question has an average attempt rate of 10:
  - In case, a child answers the quiz question incorrectly for 5 times in a row, the progress for this question is 50%.
  - In case, a child answers the quiz question incorrectly for 9 times in a row, the progress for this question is 90%.
  - In case, a child answers the quiz question incorrectly for 11 times in a row, the progress for this question is 97,5%. In this case, a child needs more attempts than the attempt average. The percentage will just slightly increase after the number of incorrect attempts is higher than the average attempt rate. Progress can only go to 100% if the child ultimately answers the question correctly.
  - Another child answers the quiz question correct within one attempt. Then the progress for this question is 100%.

Case 1: 1 Goal

At the first visit in the hospital, a child get 21 active goals. Among those goals is the goal **Food and Activity**. A child has to successfully fulfill the following tasks:

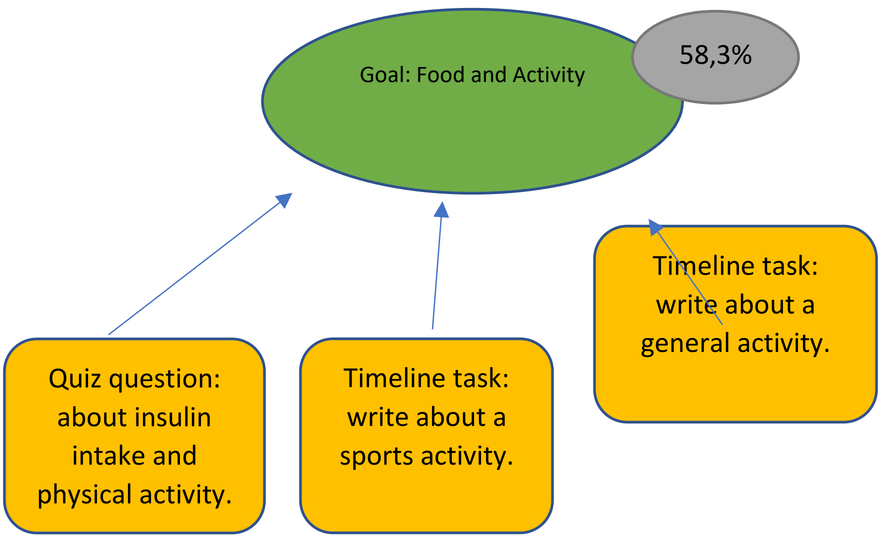
Learning Tasks

Task:	Type:	Description:	Average attempt rate
Quiz question: about insulin intake and physical activity.	Quiz question	Anwer the question: "Before sports, do you need eat extra carbohydrates or do you need to lower your insulin intake?"	2
Add activity	Timeline task	Write about a general activity	Not applicable
Add activity	Timeline task	Write about a sports activity	Not applicable

Progress

The child of this case executed the following related to the goal **Food and Activity**:

Day	Task	Outcome	Total achieved tasks	Progress
1	Add activity	Fulfilled	1	33,3%
13	Quiz question: about insulin intake and physical activity.	Unanswered	1.5	50.0%
13	Quiz question: about insulin intake and physical activity.	Unanswered	1.75	58,3%



In this case, we neglect the other goals.

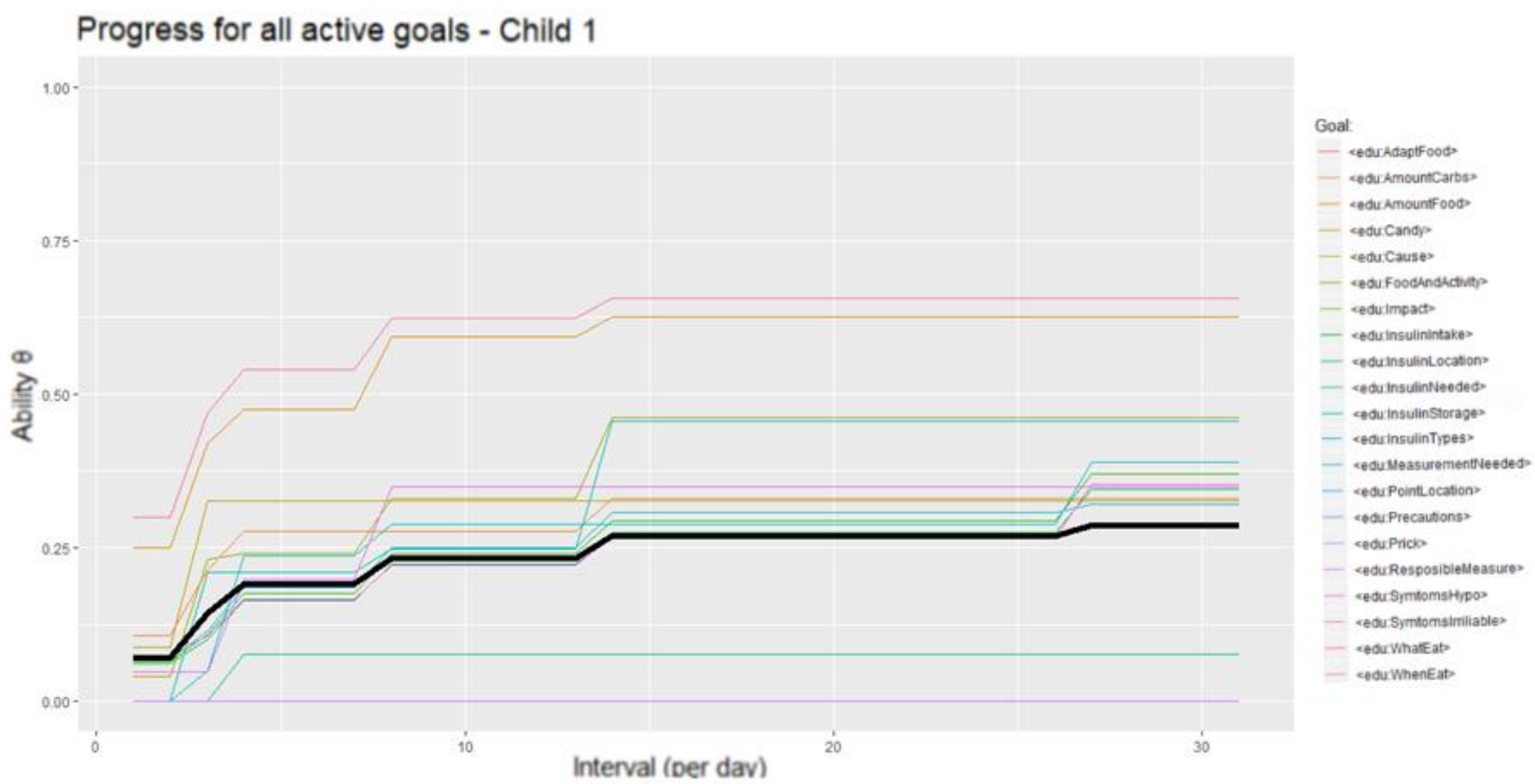
Please answer the following statements, based on (i) your expertise, (ii) the knowledge you would have from the child outside of PAL and (iii) the information that PAL would provide as given above.

	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
It is clear for me what the child's progress is.	☐	☐	☐	☐	☐
I understand how the progress is calculated.	☐	☐	☐	☐	☐
It is clear for me what I have to do to optimize the child's learning experience within the PAL system.	☐	☐	☐	☐	☐
It is clear for me, if I have to adapt the child's goal selection in the PAL system.	☐	☐	☐	☐	☐
It is clear what the child needs outside of PAL.	☐	☐	☐	☐	☐
Any additional comments / observations					

Case 2: multiple active goals

A child has 20 active goals. One month after the first visit in the hospital, the child has a meeting with you. The PAL system shows the following information related to the child's progress:

Goal	**Progress**
Food and Activity	0%
Carbohydrates	33.0%
Amount of Food	62.5%
Candy	32,6%
Cause	46,1%
Impact	0%
Insulin Intake	36,9%
Insulin Locations	34,3%
Insulin Needed	7,7%
Insulin Storage	45,6%
Insulin Types	38,9%
Measurement Needed	32,1%
Point Location	0%
Precautions	0%
Prick	0%
Symptoms Hypo	34,8%
Symptoms Irriliable	35,2%
What Eat	65,6%
When Eat	65,6%


Progress for all active goals - Child 1
Ability θ
1.00
0.75
0.50
0.25
0.00
0
10
20
30
Interval (per day)
Goal:
<edu:AdaptFood>
<edu:AmountCarbs>
<edu:AmountFood>
<edu:Candy>
<edu:Cause>
<edu:FoodAndActivity>
<edu:Impact>
<edu:InsulinIntake>
<edu:InsulinLocation>
<edu:InsulinNeeded>
<edu:InsulinStorage>
<edu:InsulinTypes>
<edu:MeasurementNeeded>
<edu:PointLocation>
<edu:Precautions>
<edu:Prick>
<edu:ResposibleMeasure>
<edu:SymtomsHypo>
<edu:SymtomsImliable>
<edu:WhatEat>
<edu:WhenEat>

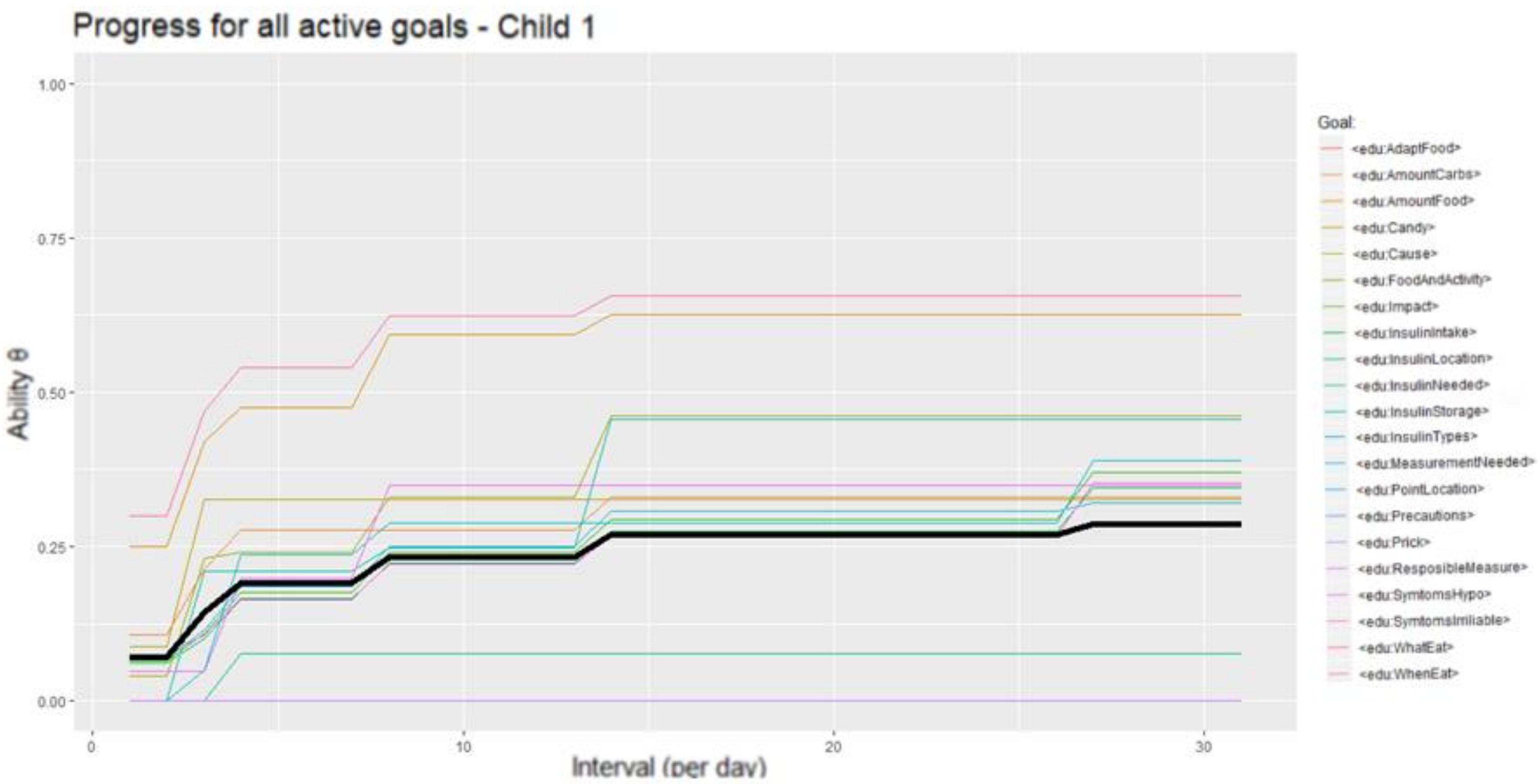
Please answer the following statements, based on (i) your expertise, (ii) the knowledge you would have from the child outside of PAL and (iii) the information that PAL would provide as given above.

	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
It is clear for me what the child's progress is.	☐	☐	☐	☐	☐
I understand how the progress is calculated.	☐	☐	☐	☐	☐
It is clear for me what I have to do to optimize the child's learning experience within the PAL system.	☐	☐	☐	☐	☐
It is clear for me, if I have to adapt the child's goal selection in the PAL system.	☐	☐	☐	☐	☐
It is clear what the child needs outside of PAL.	☐	☐	☐	☐	☐
Any additional comments / observations					

Case 3: multiple active goals 2

A child has 12 active goals. Two months after the first visit in the hospital, the child has a meeting with you. The PAL system shows the following information related to the child's progress:

Goal	**Progress**
Carbohydrates	88,0%
Cause	100%
Correct Hypo 1	91,2%
Inject	0%
Insulin Intake	89,5%
Insulin Location	87,5%
Why Measure	84,7%
Measure Value	88,5%
Point Location	0%
Prepare Meter	0%
Prick	0%
Response	76,6%
Symptoms Hypo	60,2%


Progress for all active goals - Child 1
Ability θ
1.00
0.75
0.50
0.25
0.00
0
10
20
30
Interval (per day)
Goal:
<edu:AdaptFood>
<edu:AmountCarbs>
<edu:AmountFood>
<edu:Candy>
<edu:Cause>
<edu:FoodAndActivity>
<edu:Impact>
<edu:InsulinIntake>
<edu:InsulinLocation>
<edu:InsulinNeeded>
<edu:InsulinStorage>
<edu:InsulinTypes>
<edu:MeasurementNeeded>
<edu:PointLocation>
<edu:Precautions>
<edu:Prick>
<edu:ResposibleMeasure>
<edu:SymtomsHypo>
<edu:SymtomsImliable>
<edu:WhatEat>
<edu:WhenEat>

Please answer the following statements, based on (i) your expertise, (ii) the knowledge you would have from the child outside of PAL and (iii) the information that PAL would provide as given above.

	Strongly disagree	Disagree	Neutral	Agree	Strongly Agree
It is clear for me what the child's progress is.	☐	☐	☐	☐	☐
I understand how the progress is calculated.	☐	☐	☐	☐	☐
It is clear for me what I have to do to optimize the child's learning experience within the PAL system.	☐	☐	☐	☐	☐
It is clear for me, if I have to adapt the child's goal selection in the PAL system.	☐	☐	☐	☐	☐
It is clear what the child needs outside of PAL.	☐	☐	☐	☐	☐
Any additional comments / observations					

Semi-structured interviews - questionnaire transcriptions

Doel van deze vragenlijst is om te inventariseren welke elementen in een voortgangsmaat binnen het PAL project van belang zijn.

ENQUETE VOORTGANGSMAAT PAL

Datum (dd[redacted]

Naam: [redacted]

Functie: [redacted]ent kinderdiabetes

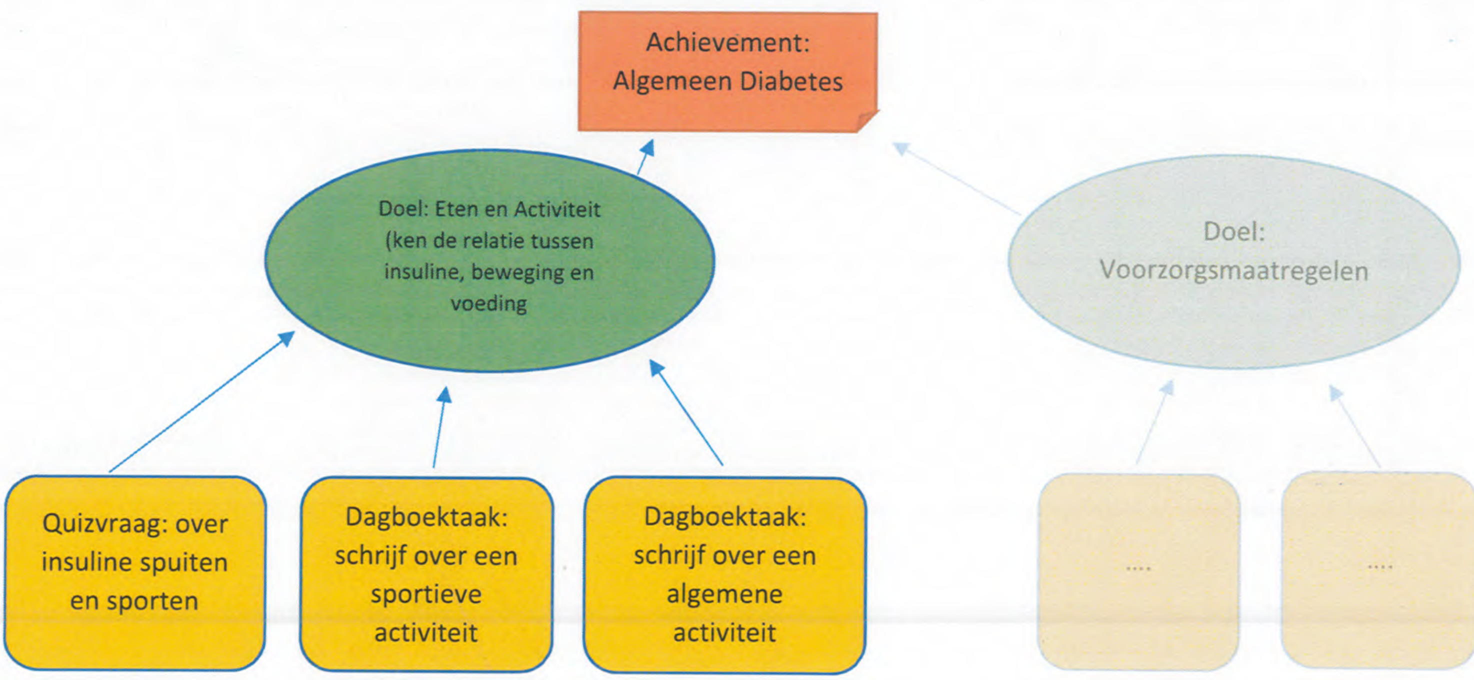
	Erg Weinig	Weinig	Niet veel/Niet weinig	Veel	Erg Veel
Ervaring met PAL systeem:	☐	☐	☒	☐	☐
Hoe vaak heeft u contact met een kind dat het PAL systeem gebruikt?	tijdens pal alleen als kinderen hier zijn. 8 kinderen. normaal iedere 3 mnd zonodig vaker.				

PAL Systeem

De educatie van PAL is doel gestuurd. Een kind kan een of meerdere doelen hebben geactiveerd.

Een doel wordt behaald door alle bijbehorende taken correct af te ronden. Bij het behalen van een combinatie van doelen kan het kind ook een achievement behalen.

Voorbeeld: het doel **Eten en Activiteit** gaat over relatie tussen insuline, beweging en voeding. Het doel wordt bereikt door drie taken te voltooien: 1 quizvraag over koolhydraten en 2 dagboektaken. Indien een kind naast het doel **Eten en Activiteit** ook het doel **Voorzorgsmaatregelen** behaalt, krijgt het kind het achievement **Algemeen Diabetes**. (zie onderstaand diagram)



Er zijn meerdere soorten taken zoals quizvragen, dagboektaken en spelletjestaken. Hierboven een indruk van de PAL app.

Belangrijke elementen van een voortgangsmaat

Als u zou mogen bepalen welke informatie het PAL systeem u zou tonen over de voortgang van het kind, d.w.z. informatie waarmee u de voortgang van het kind kunt evalueren. Welke informatie zou u dan willen zien?

Graag zou ik via Palsysteem willen zien
of het kind regelmatig het systeem
gebruikt
Zorg het voor vooruitgang
Is er uitdaging genoeg waardoor
kinderen gemotiveerd blijven
Verbetering van waarde HbA1c

Kunt u de onderwerpen uit het antwoord op de vorige vraag rangschikken op prioriteit?

1. hoe vaak wordt het gebruikt
2. zit er vooruitgang in
3. uitdaging
4. motivatie
5. waarde verbetering
6. HbA1c
7. ....
8. ....

Hoe vaak zou u de voortgang van een kind willen bekijken?

1 x per week.

En over welke periode zou u de voortgang willen evalueren?

maandelijks.

Werking van de voorgangsmaat

- De voortgang wordt per doel gemeten en uitgedrukt in een percentage.
- Het percentage wordt bepaald door het aantal taken dat is afgerond voor een doel.
- Voor de quizvraag geldt een kleine nuancering: elke quizvraag heeft een pogingsgemiddelde. Het pogingsgemiddelde is het aantal keer dat een kind gemiddeld nodig heeft om de quizvraag juist te beantwoorden. Pogingsgemiddelde wordt meegenomen in het berekenen van de voortgang voor een quizvraag.

  Een voorbeeld:
  Een quizvraag heeft een pogingsgemiddelde van 10:
  - Een kind beantwoordt de quizvraag 5 keer achter elkaar fout. Dan is de voortgang voor deze vraag 50%.
  - Een kind beantwoordt de quizvraag 9 keer achter elkaar fout. Dan is de voortgang voor deze vraag 90%.
  - Een kind beantwoordt de quizvraag 11 keer achter elkaar fout. Dan is de voortgang voor deze vraag 97.5%. Bij het vaker fout beantwoorden dan het pogingsgemiddelde loopt het percentage heel lichtjes op. De voortgang kan alleen naar 100% gaan als het kind de vraag uiteindelijk goed beantwoordt.
  - Een ander kind beantwoordt de quizvraag in 1 keer goed. Dan is de voortgang voor deze vraag 100%.

Casus 1: 1 Doel

Een kind krijgt bij zijn eerste afspraak 21 actieve doelen, o.a. het doel **Eten en Activiteit**. Voor het doel Eten en Activiteit moet het kind de volgende taken volbrengen:

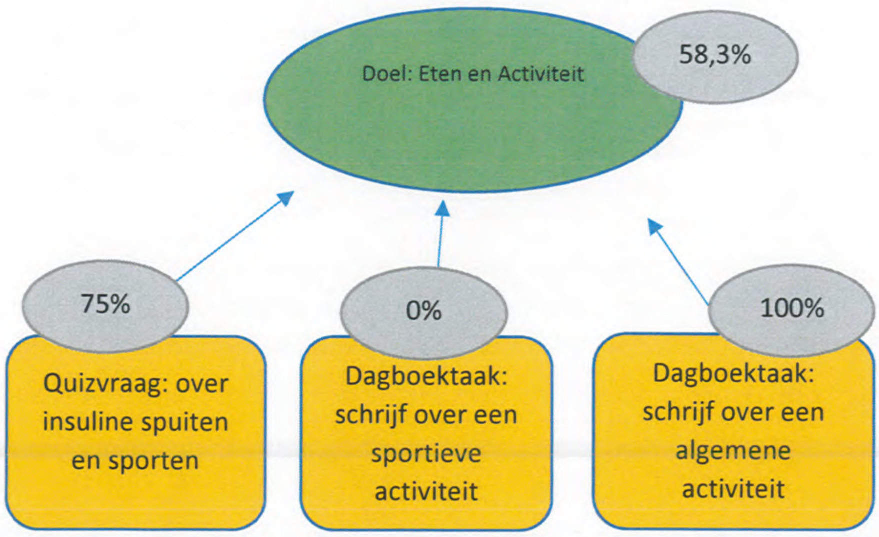
Taken

Taak:	Type:	Omschrijving:	Pogingsgemiddelde:
Quizvraag over insuline spuiten en sporten	Quizvraag	Beantwoord de vraag: "Moet je extra koolhydraten eten of minder spuiten/bolussen voordat je gaat sporten."	2
Activiteit toevoegen	Dagboektaak	Schrijf over een algemene activiteit.	n.v.t.
Sport toevoegen	Dagboektaak	Schrijf over een sportieve activiteit	n.v.t.

Voortgang

Het kind heeft na 2 weken het volgende uitgevoerd met betrekking tot het doel **Eten en Activiteit**:

Dag	Taak	Uitkomst	Totaal behaalde taken	Voortgang
1	Activiteit toevoegen	Afgerond	1	33,3%
13	Quizvraag over insuline spuiten en sporten	Onbeantwoord	1.5	50.0%
13	Quizvraag over insuline spuiten en sporten	Onbeantwoord	1.75	58,3%



In deze casus negeren we even de andere actieve doelen.

Kunt u op basis van (i) uw expertise, (ii) de kennis die u van het kind zou hebben buiten PAL om en (iii) de gegevens die PAL u toont zoals bovenstaand voorbeeld onderstaande stellingen beantwoorden?

	Sterk mee oneens	Mee oneens	Neutraal	Mee eens	Sterk mee eens
Het is voor mij duidelijk wat de voortgang is van het kind.	☐	☐	☐	☒	☐
Ik begrijp hoe de voortgang wordt berekend door PAL.	☐	☐	☐	☒	☐
Het is voor mij duidelijk wat ik moet doen om het kind maximaal te laten leren van het PAL systeem.	☐	☐	☐	☒	☐
Het is voor mij duidelijk of ik een aanpassing moet maken in de doelen selectie voor dit kind binnen PAL.	☐	☐	☐	☒	☐
Het is mij duidelijk wat het kind nodig heeft buiten het PAL systeem om.	☐	☐	☐	☒	☐

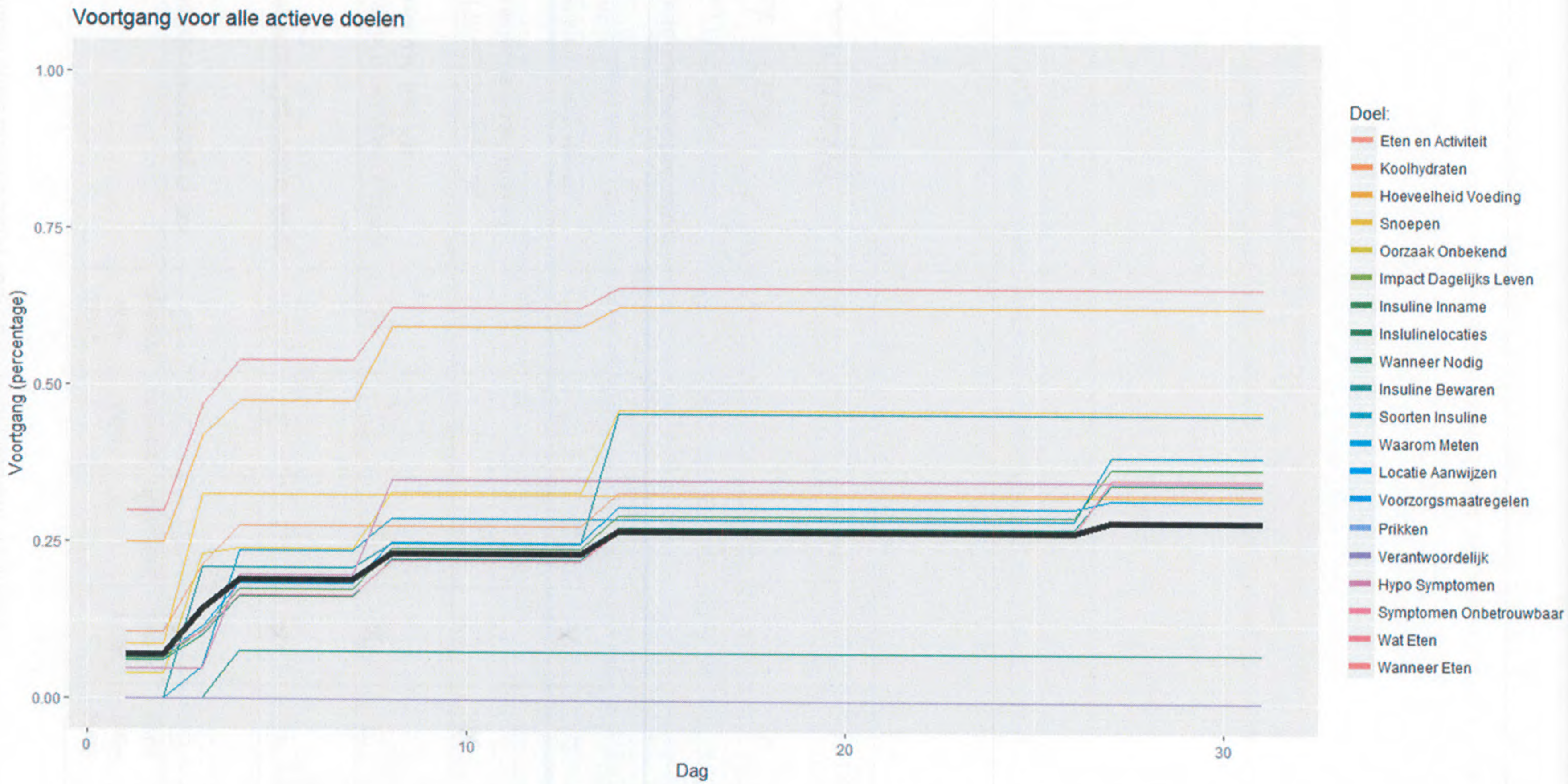
Eventueel aanvullende opmerkingen/observaties

Regelmatig mee kijken met doelen is belangrijk om inzicht in voortgang te krijgen

Casus 2: Meerdere actieve doelen

Een kind heeft 20 actieve doelen. 1 maand na de eerste afspraak komt het kind langs bij u. Het PAL systeem laat u de volgende gegevens zien:

Doel	**Voortgang**
Eten en Activiteit	0%
Koolhydraten	33.0%
Hoeveelheid Voeding	62.5%
Snoepen	32,6%
Oorzaak Onbekend	46,1%
Impact Dagelijks Leven	0%
Insuline Inname	36,9%
Insulinelocaties	34,3%
Wanneer Nodig	7,7%
Insuline Bewaren	45,6%
Soorten Insuline	38,9%
Waarom Meten	32,1%
Locatie Aanwijzen	0%
Voorzorgsmaatregelen	0%
Prikken	0%
Hypo Symptomen	34,8%
Symptomen Onbetrouwbaar	35,2%
Wat Eten	65,6%
Wanneer Eten	65,6%



Voortgang voor alle actieve doelen
Voortgang (percentage)
1.00
0.75
0.50
0.25
0.00
0
10
20
30
Dag
Doel:
Eten en Activiteit
Koolhydraten
Hoeveelheid Voeding
Snoepen
Oorzaak Onbekend
Impact Dagelijks Leven
Insuline Inname
Inslulinelocaties
Wanneer Nodig
Insuline Bewaren
Soorten Insuline
Waarom Meten
Locatie Aanwijzen
Voorzorgsmaatregelen
Prikken
Verantwoordelijk
Hypo Symptomen
Symptomen Onbetrouwbaar
Wat Eten
Wanneer Eten

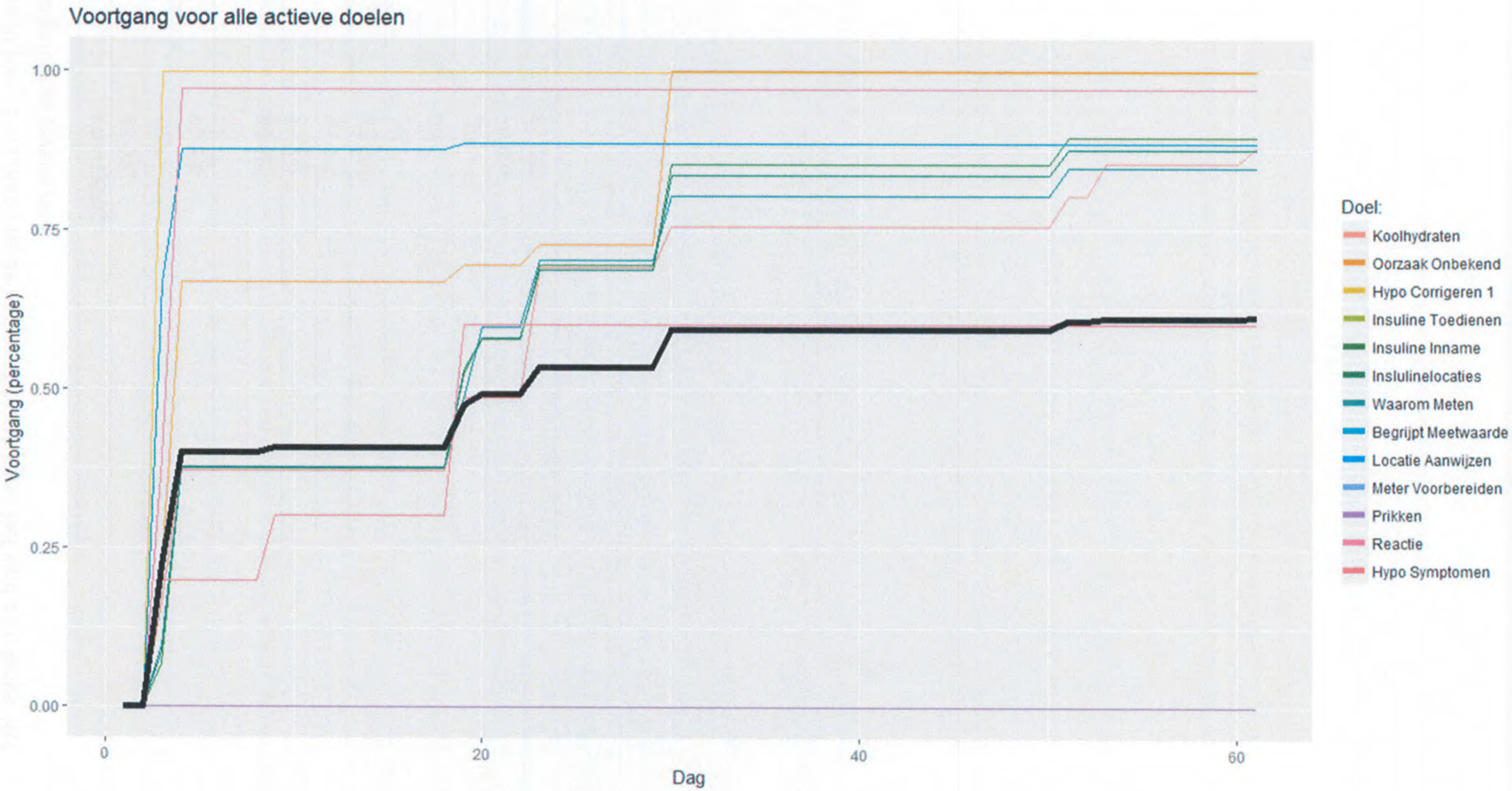
Kunt u op basis van (i) uw expertise, (ii) de kennis die u van het kind zou hebben buiten PAL om en (iii) de gegevens die PAL u toont zoals bovenstaand voorbeeld onderstaande stellingen beantwoorden?

	Sterk mee oneens	Mee oneens	Neutraal	Mee eens	Sterk mee eens
Het is voor mij duidelijk wat de voortgang is van het kind.	☐	☐	☐	☒	☐
Ik begrijp hoe de voortgang wordt berekend door PAL.	☐	☐	☐	☒	☐
Het is voor mij duidelijk wat ik moet doen om het kind maximaal te laten leren van het PAL systeem.	☐	☐	☐	☒	☐
Het is voor mij duidelijk of ik een aanpassing moet maken in de doelen selectie voor dit kind binnen PAL.	☐	☐	☐	☐	☒
Het is mij duidelijk wat het kind nodig heeft buiten het PAL systeem om.	☐	☐	☐	☒	☐
Eventueel aanvullende opmerkingen/observaties blyven stimuleren maakt dat een kind vooruitgang boekt.					

Casus 3: Meerdere actieve doelen 2

Een kind heeft 12 actieve doelen. 2 maanden na de eerste afspraak komt het kind bij u langs. Het PAL systeem laat u de volgende gegevens zien:

Doel	Voortgang
Koolhydraten	88,0%
Oorzaak Onbekend	100%
Hypo Corrigeren 1	91,2%
Insuline Toedienen	0%
Insuline Inname	89,5%
Insulinelocaties	87,5%
Waarom Meten	84,7%
Begrijpt Meetwaarde	88,5%
Locatie Aanwijzen	0%
Meter Voorbereiden	0%
Prikken	0%
Reactie	76,6%
Hypo Symptomen	60,2%


Voortgang voor alle actieve doelen
Voortgang (percentage)
1.00
0.75
0.50
0.25
0.00
0
20
40
60
Dag
Doel:
Koolhydraten
Oorzaak Onbekend
Hypo Corrigeren 1
Insuline Toedienen
Insuline Inname
Inslulinelocaties
Waarom Meten
Begrijpt Meetwaarde
Locatie Aanwijzen
Meter Voorbereiden
Prikken
Reactie
Hypo Symptomen

Kunt u op basis van (i) uw expertise, (ii) de kennis die u van het kind zou hebben buiten PAL om en (iii) de gegevens die PAL u toont zoals bovenstaand voorbeeld onderstaande stellingen beantwoorden?

	Sterk mee oneens	Mee oneens	Neutraal	Mee eens	Sterk mee eens
Het is voor mij duidelijk wat de voortgang is van het kind.	☐	☐	☐	☒	☐
Ik begrijp hoe de voortgang wordt berekend door PAL.	☐	☐	☐	☐	☒
Het is voor mij duidelijk wat ik moet doen om het kind maximaal te laten leren van het PAL systeem.	☐	☐	☐	☐	☒
Het is voor mij duidelijk of ik een aanpassing moet maken in de doelen selectie voor dit kind binnen PAL.	☐	☐	☐	☐	☒
Het is mij duidelijk wat het kind nodig heeft buiten het PAL systeem om.	☐	☐	☐	☐	☒
Eventueel aanvullende opmerkingen/observaties Je ziet bij regelmatig contact dat groot deel van de doelen vooruitgang boekt.					

Doel van deze vragenlijst is om te inventariseren welke elementen in een voortgangsmaat binnen het PAL project van belang zijn.

ENQUETE VOORTGANGSMAAT PAL

Datum (dd/m

Naam:

Functie: gkundige

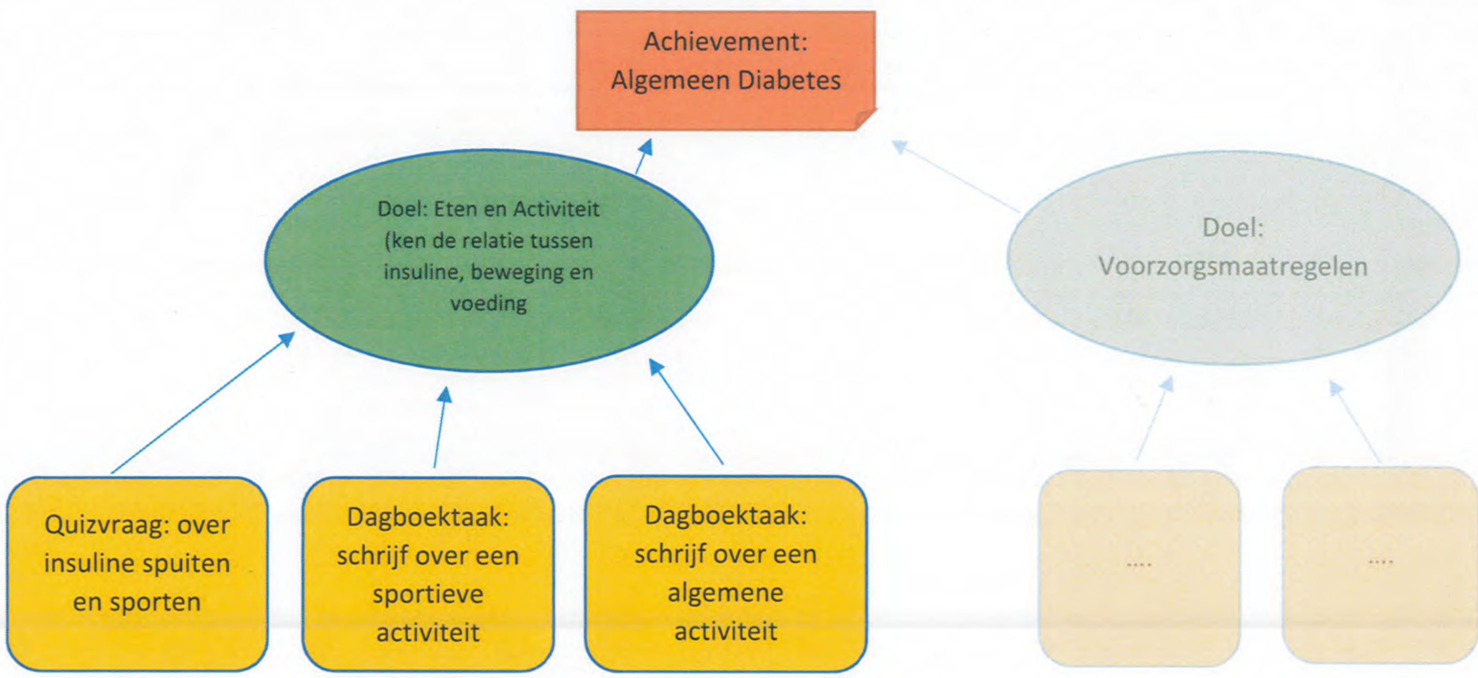
	Erg Weinig	Weinig	Niet veel/Niet weinig	Veel	Erg Veel
Ervaring met PAL systeem:	☐	☐	☒	☐	☐
Hoe vaak heeft u contact met een kind dat het PAL systeem gebruikt?	3x op de poli + nauragen hoe het gaat tussendoor.				

PAL Systeem

De educatie van PAL is doel gestuurd. Een kind kan een of meerdere doelen hebben geactiveerd.

Een doel wordt behaald door alle bijbehorende taken correct af te ronden. Bij het behalen van een combinatie van doelen kan het kind ook een achievement behalen.

Voorbeeld: het doel **Eten en Activiteit** gaat over relatie tussen insuline, beweging en voeding. Het doel wordt bereikt door drie taken te voltooien: 1 quizvraag over koolhydraten en 2 dagboektaken. Indien een kind naast het doel **Eten en Activiteit** ook het doel **Voorzorgsmaatregelen** behaalt, krijgt het kind het achievement **Algemeen Diabetes**. (zie onderstaand diagram)



Er zijn meerdere soorten taken zoals quizvragen, dagboektaken en spelletjestaken. Hierboven een indruk van de PAL app.

Belangrijke elementen van een voortgangsmaat

Als u zou mogen bepalen welke informatie het PAL systeem u zou tonen over de voortgang van het kind, d.w.z. informatie waarmee u de voortgang van het kind kunt evalueren. Welke informatie zou u dan willen zien?

1 - welke doelen behaald zijn
2 - wat kind meest heeft gedaan / het liefste doet.
3 - wat vullen ze in qua waardes end.

Kunt u de onderwerpen uit het antwoord op de vorige vraag rangschikken op prioriteit?

1. 1
2. 3
3. 2
4. ....
5. ....
6. ....
7. ....
8. ....

Hoe vaak zou u de voortgang van een kind willen bekijken?

- zou fijn zijn als je bijv. mail krijgt als er iets is afgerond / of er niets is gedaan enz.
- bijv 1x per maand bericht.
zo blijf je zelf ~~ak~~ ook aktief met PAL bezig.

En over welke periode zou u de voortgang willen evalueren?

- per maand de aktiviteiten.
- dan kan je weer nieuwe doelen openen.
blyft het voor het kind ook leuk.

Werking van de voorgangsmaat

- De voortgang wordt per doel gemeten en uitgedrukt in een percentage.
- Het percentage wordt bepaald door het aantal taken dat is afgerond voor een doel.
- Voor de quizvraag geldt een kleine nuancering: elke quizvraag heeft een pogingsgemiddelde. Het pogingsgemiddelde is het aantal keer dat een kind gemiddeld nodig heeft om de quizvraag juist te beantwoorden. Pogingsgemiddelde wordt meegenomen in het berekenen van de voortgang voor een quizvraag.

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  - Een kind beantwoordt de quizvraag 9 keer achter elkaar fout. Dan is de voortgang voor deze vraag 90%.
  - Een kind beantwoordt de quizvraag 11 keer achter elkaar fout. Dan is de voortgang voor deze vraag 97.5%. Bij het vaker fout beantwoorden dan het pogingsgemiddelde loopt het percentage heel lichtjes op. De voortgang kan alleen naar 100% gaan als het kind de vraag uiteindelijk goed beantwoordt.
  - Een ander kind beantwoordt de quizvraag in 1 keer goed. Dan is de voortgang voor deze vraag 100%.

Casus 1: 1 Doel

Een kind krijgt bij zijn eerste afspraak 21 actieve doelen, o.a. het doel **Eten en Activiteit**. Voor het doel Eten en Activiteit moet het kind de volgende taken volbrengen:

Taken

Taak:	Type:	Omschrijving:	Pogingsgemiddelde:
Quizvraag over insuline spuiten en sporten	Quizvraag	Beantwoord de vraag: "Moet je extra koolhydraten eten of minder spuiten/bolussen voordat je gaat sporten."	2
Activiteit toevoegen	Dagboektaak	Schrijf over een algemene activiteit.	n.v.t.
Sport toevoegen	Dagboektaak	Schrijf over een sportieve activiteit	n.v.t.

Voortgang

Het kind heeft na 2 weken het volgende uitgevoerd met betrekking tot het doel **Eten en Activiteit**:

Dag	Taak	Uitkomst	Totaal behaalde taken	Voortgang
1	Activiteit toevoegen	Afgerond	1	33,3%
13	Quizvraag over insuline spuiten en sporten	Onbeantwoord	1.5	50.0%
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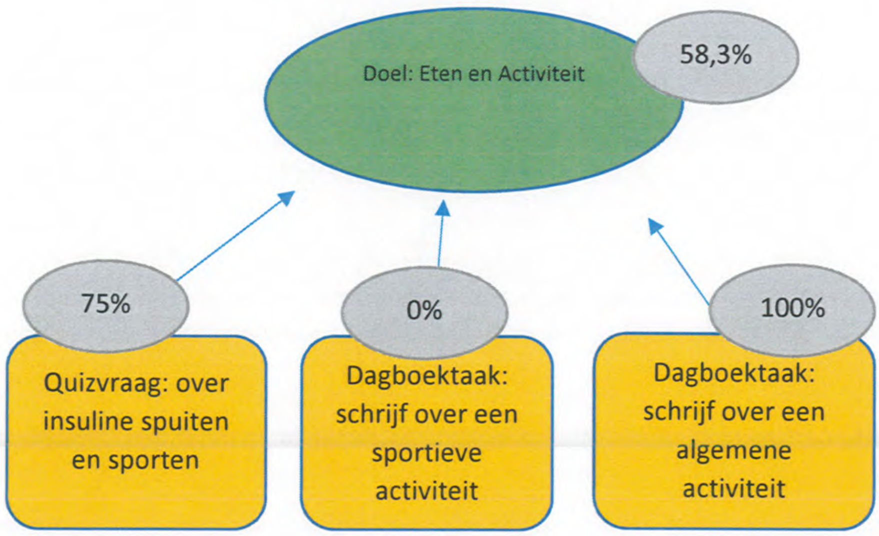


In deze casus negeren we even de andere actieve doelen.

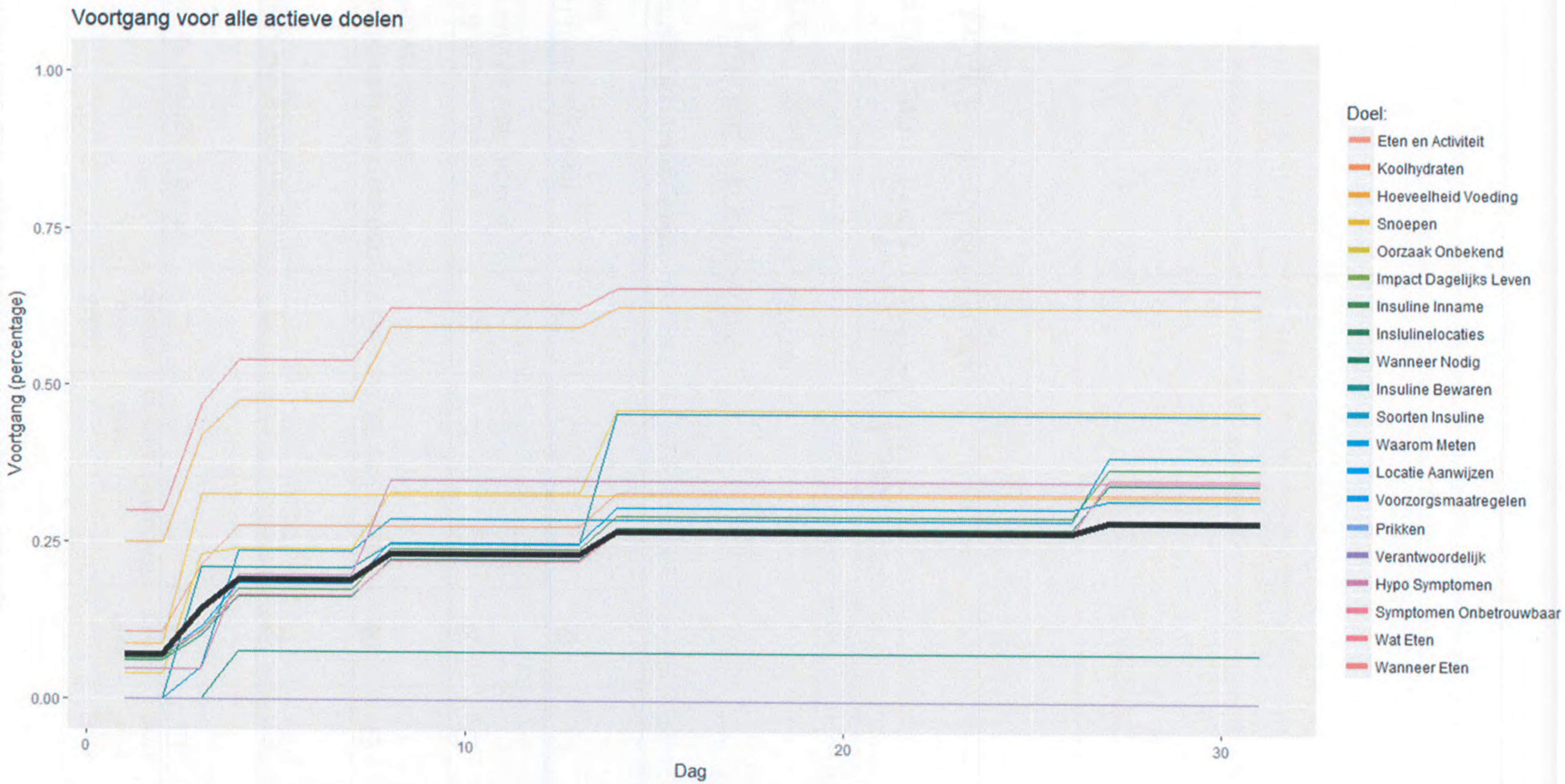
Kunt u op basis van (i) uw expertise, (ii) de kennis die u van het kind zou hebben buiten PAL om en (iii) de gegevens die PAL u toont zoals bovenstaand voorbeeld onderstaande stellingen beantwoorden?

	Sterk mee oneens	Mee oneens	Neutraal	Mee eens	Sterk mee eens
Het is voor mij duidelijk wat de voortgang is van het kind.	☐	~~☒~~	☐	☒	☐
Ik begrijp hoe de voortgang wordt berekend door PAL.	☐	~~☒~~	☐	☒	☐
Het is voor mij duidelijk wat ik moet doen om het kind maximaal te laten leren van het PAL systeem.	☐	☐	☐	☒	☐
Het is voor mij duidelijk of ik een aanpassing moet maken in de doelen selectie voor dit kind binnen PAL.	☐	☐	☐	☒	☐
Het is mij duidelijk wat het kind nodig heeft buiten het PAL systeem om.	☐	☐	☐	☒	☐
Eventueel aanvullende opmerkingen/observaties					

Casus 2: Meerdere actieve doelen

Een kind heeft 20 actieve doelen. 1 maand na de eerste afspraak komt het kind langs bij u. Het PAL systeem laat u de volgende gegevens zien:

Doel	Voortgang
Eten en Activiteit	0%
Koolhydraten	33.0%
Hoeveelheid Voeding	62.5%
Snoepen	32,6%
Oorzaak Onbekend	46,1%
Impact Dagelijks Leven	0%
Insuline Inname	36,9%
Insulinelocaties	34,3%
Wanneer Nodig	7,7%
Insuline Bewaren	45,6%
Soorten Insuline	38,9%
Waarom Meten	32,1%
Locatie Aanwijzen	0%
Voorzorgsmaatregelen	0%
Prikken	0%
Hypo Symptomen	34,8%
Symptomen Onbetrouwbaar	35,2%
Wat Eten	65,6%
Wanneer Eten	65,6%



Voortgang voor alle actieve doelen
Voortgang (percentage)
1.00
0.75
0.50
0.25
0.00
0
10
20
30
Dag
Doel:
Eten en Activiteit
Koolhydraten
Hoeveelheid Voeding
Snoepen
Oorzaak Onbekend
Impact Dagelijks Leven
Insuline Inname
Inslulinelocaties
Wanneer Nodig
Insuline Bewaren
Soorten Insuline
Waarom Meten
Locatie Aanwijzen
Voorzorgsmaatregelen
Prikken
Verantwoordelijk
Hypo Symptomen
Symptomen Onbetrouwbaar
Wat Eten
Wanneer Eten

Kunt u op basis van (i) uw expertise, (ii) de kennis die u van het kind zou hebben buiten PAL om en (iii) de gegevens die PAL u toont zoals bovenstaand voorbeeld onderstaande stellingen beantwoorden?

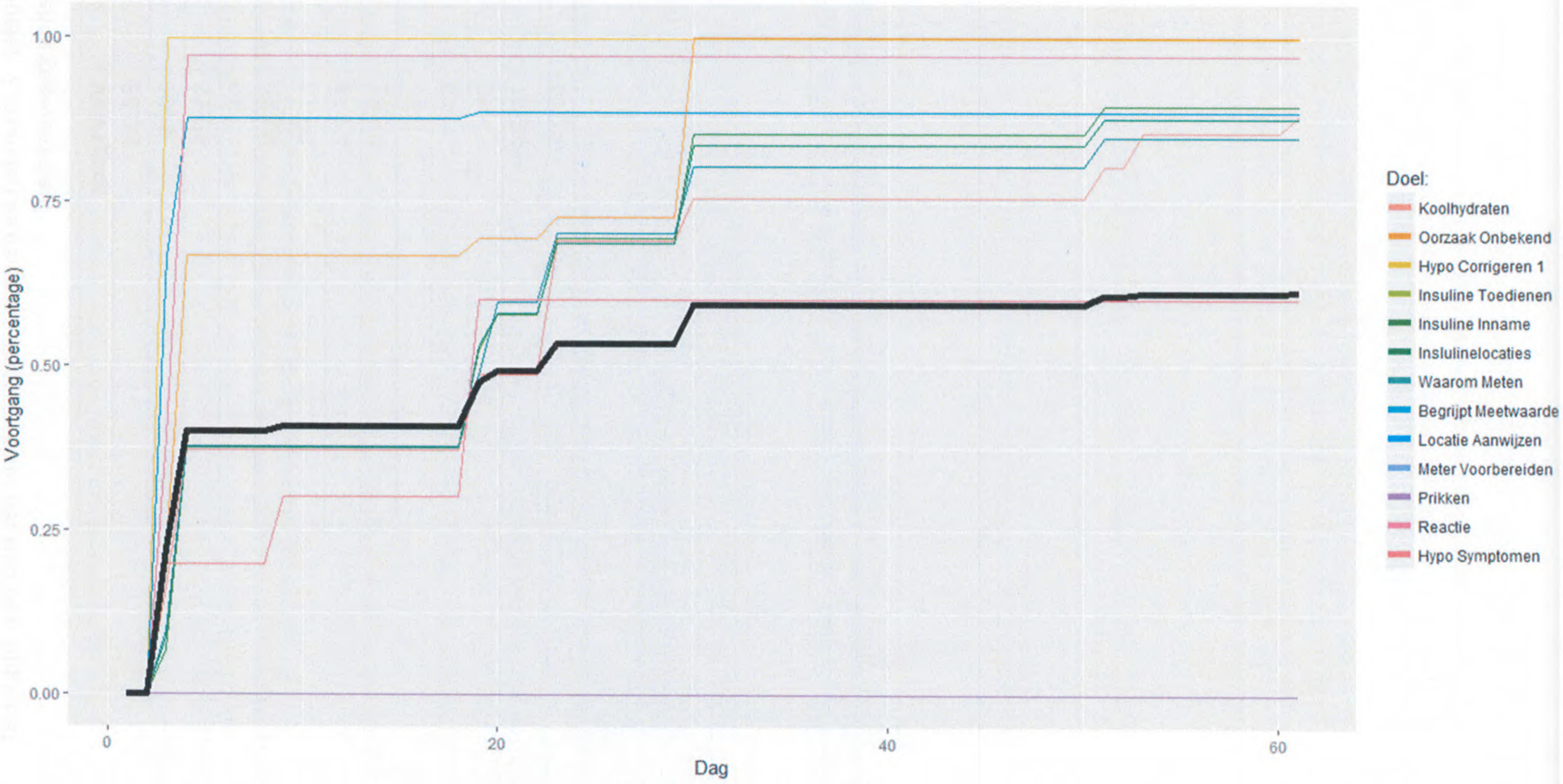
	Sterk mee oneens	Mee oneens	Neutraal	Mee eens	Sterk mee eens
Het is voor mij duidelijk wat de voortgang is van het kind.	☐	☐	☐	☒	☐
Ik begrijp hoe de voortgang wordt berekend door PAL.	☐	☐	☐	☒	☐
Het is voor mij duidelijk wat ik moet doen om het kind maximaal te laten leren van het PAL systeem.	☐	☐	☐	☒	☐
Het is voor mij duidelijk of ik een aanpassing moet maken in de doelen selectie voor dit kind binnen PAL.	☐	☐	☐	☒	☐
Het is mij duidelijk wat het kind nodig heeft buiten het PAL systeem om.	☐	☐	☐	☒	☐
Eventueel aanvullende opmerkingen/observaties - vaak zie je flinke motivatie bij start, maar zakt het erna in. Aktief benaderen met tablet/PAL te werken blijft belangrijk.					

Casus 3: Meerdere actieve doelen 2

Een kind heeft 12 actieve doelen. 2 maanden na de eerste afspraak komt het kind bij u langs. Het PAL systeem laat u de volgende gegevens zien:

Doel	**Voortgang**
Koolhydraten	88,0%
Oorzaak Onbekend	100%
Hypo Corrigeren 1	91,2%
Insuline Toedienen	0%
Insuline Inname	89,5%
Insulinelocaties	87,5%
Waarom Meten	84,7%
Begrijpt Meetwaarde	88,5%
Locatie Aanwijzen	0%
Meter Voorbereiden	0%
Prikken	0%
Reactie	76,6%
Hypo Symptomen	60,2%

Voortgang voor alle actieve doelen



Kunt u op basis van (i) uw expertise, (ii) de kennis die u van het kind zou hebben buiten PAL om en (iii) de gegevens die PAL u toont zoals bovenstaand voorbeeld onderstaande stellingen beantwoorden?

	Sterk mee oneens	Mee oneens	Neutraal	Mee eens	Sterk mee eens
Het is voor mij duidelijk wat de voortgang is van het kind.	☐	☐	☐	☒	☐
Ik begrijp hoe de voortgang wordt berekend door PAL.	☐	☐	☐	☒	☐
Het is voor mij duidelijk wat ik moet doen om het kind maximaal te laten leren van het PAL systeem.	☐	☐	☐	☒	☐
Het is voor mij duidelijk of ik een aanpassing moet maken in de doelen selectie voor dit kind binnen PAL.	☐	☐	☐	☒	☐
Het is mij duidelijk wat het kind nodig heeft buiten het PAL systeem om.	☐	☐	☐	☒	☐

Eventueel aanvullende opmerkingen/observaties

- blijven wijzen op taken die nog uitgevoerd moeten worden (lage scores)
- aan de hand van de score nagaan of er meer doelen openmoeten.
- navragen bij kind waarom sommige doelen niet behaald zijn (nog niet aan toe gekomen / te lastig?)

Doel van deze vragenlijst is om te inventariseren welke elementen in een voortgangsmaat binnen het PAL project van belang zijn.

ENQUETE VOORTGANGSMAAT PAL

Datum ([redacted]

Naam: [redacted]

Functie: [redacted]

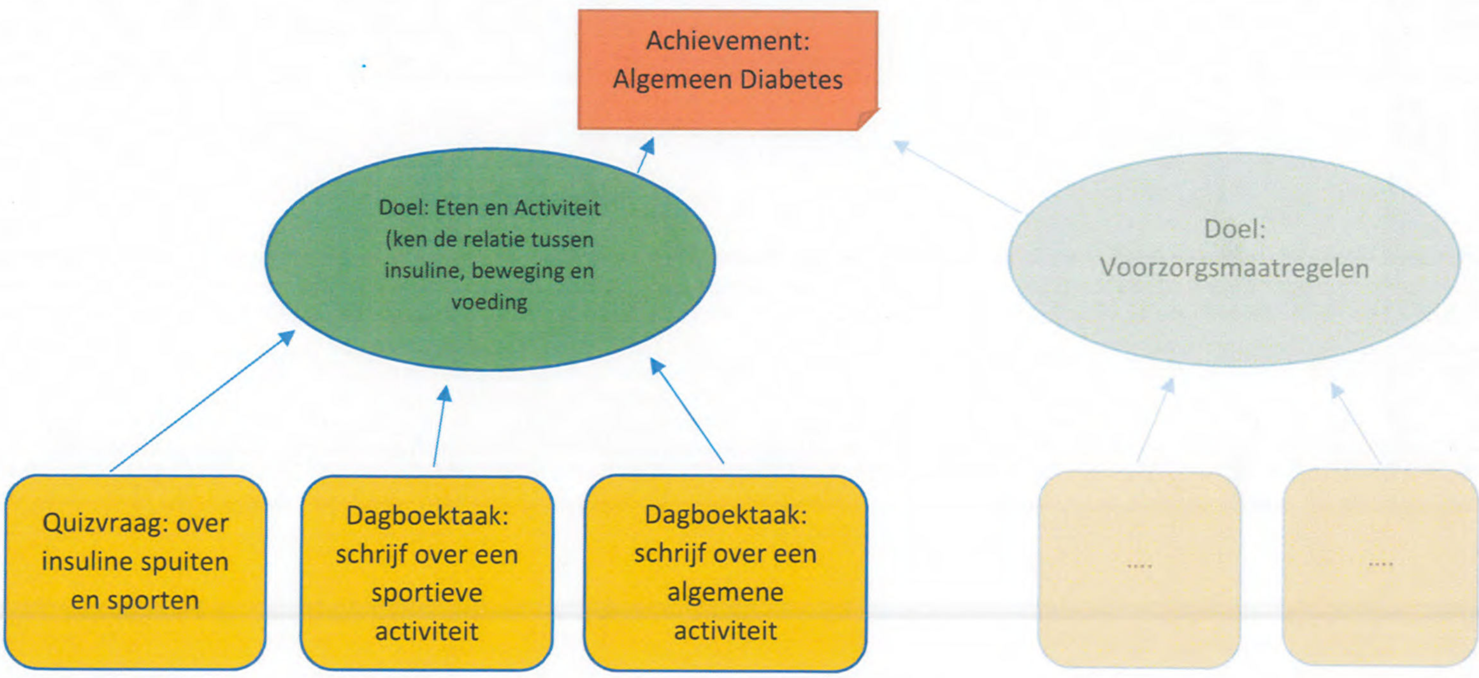
	Erg Weinig	Weinig	Niet veel/Niet weinig	Veel	Erg Veel
Ervaring met PAL systeem:	☐	☐	☐	☒	☒
Hoe vaak heeft u contact met een kind dat het PAL systeem gebruikt?	2 x per 3mnd .				

PAL Systeem

De educatie van PAL is doel gestuurd. Een kind kan een of meerdere doelen hebben geactiveerd.

Een doel wordt behaald door alle bijbehorende taken correct af te ronden. Bij het behalen van een combinatie van doelen kan het kind ook een achievement behalen.

Voorbeeld: het doel **Eten en Activiteit** gaat over relatie tussen insuline, beweging en voeding. Het doel wordt bereikt door drie taken te voltooien: 1 quizvraag over koolhydraten en 2 dagboektaken. Indien een kind naast het doel **Eten en Activiteit** ook het doel **Voorzorgsmaatregelen** behaalt, krijgt het kind het achievement **Algemeen Diabetes**. (zie onderstaand diagram)



Er zijn meerdere soorten taken zoals quizvragen, dagboektaken en spelletjestaken. Hierboven een indruk van de PAL app.

Belangrijke elementen van een voortgangsmaat

Als u zou mogen bepalen welke informatie het PAL systeem u zou tonen over de voortgang van het kind, d.w.z. informatie waarmee u de voortgang van het kind kunt evalueren. Welke informatie zou u dan willen zien?

1 welke doelen + achievements ze hebben behaald.

2 welke life events hv zelf hebben gemeten, pompsetje verwisselend.

1 of ze het leuk vinden ja/nee verveling.

3 hapening ja/nee in systeem. tabl + vraag? ook de technich.

Kunt u de onderwerpen uit het antwoord op de vorige vraag rangschikken op prioriteit?

1. ....
2. ....
3. ....
4. ....
5. ....
6. ....
7. ....
8. ....

Hoe vaak zou u de voortgang van een kind willen bekijken?

maandelijks

En over welke periode zou u de voortgang willen evalueren?

1 maand.

Werking van de voorgangsmaat

- De voortgang wordt per doel gemeten en uitgedrukt in een percentage.
- Het percentage wordt bepaald door het aantal taken dat is afgerond voor een doel.
- Voor de quizvraag geldt een kleine nuancering: elke quizvraag heeft een pogingsgemiddelde. Het pogingsgemiddelde is het aantal keer dat een kind gemiddeld nodig heeft om de quizvraag juist te beantwoorden. Pogingsgemiddelde wordt meegenomen in het berekenen van de voortgang voor een quizvraag.

  Een voorbeeld:
  Een quizvraag heeft een pogingsgemiddelde van 10:
  - Een kind beantwoordt de quizvraag 5 keer achter elkaar fout. Dan is de voortgang voor deze vraag 50%.
  - Een kind beantwoordt de quizvraag 9 keer achter elkaar fout. Dan is de voortgang voor deze vraag 90%.
  - Een kind beantwoordt de quizvraag 11 keer achter elkaar fout. Dan is de voortgang voor deze vraag 97.5%. Bij het vaker fout beantwoorden dan het pogingsgemiddelde loopt het percentage heel lichtjes op. De voortgang kan alleen naar 100% gaan als het kind de vraag uiteindelijk goed beantwoordt.
  - Een ander kind beantwoordt de quizvraag in 1 keer goed. Dan is de voortgang voor deze vraag 100%.

Casus 1: 1 Doel

Een kind krijgt bij zijn eerste afspraak 21 actieve doelen, o.a. het doel **Eten en Activiteit**. Voor het doel Eten en Activiteit moet het kind de volgende taken volbrengen:

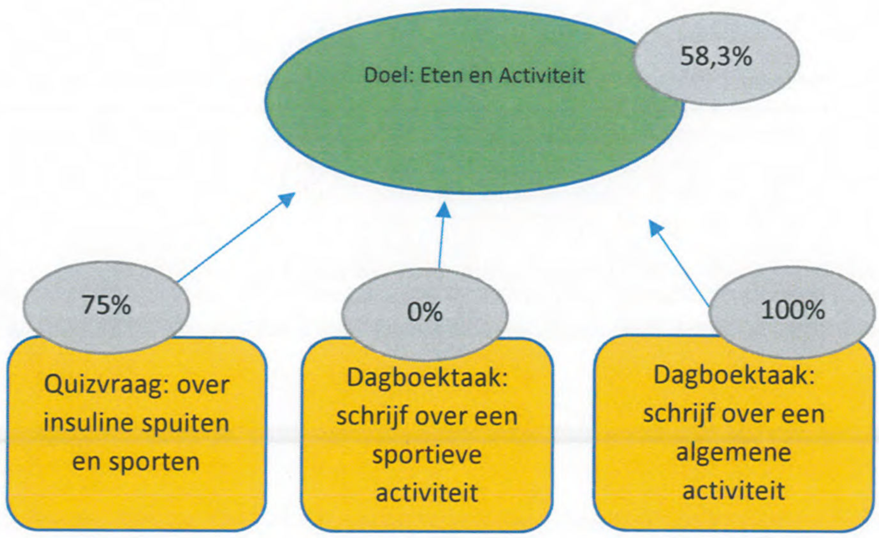
Taken

Taak:	Type:	Omschrijving:	Pogingsgemiddelde:
Quizvraag over insuline spuiten en sporten	Quizvraag	Beantwoord de vraag: "Moet je extra koolhydraten eten of minder spuiten/bolussen voordat je gaat sporten."	2
Activiteit toevoegen	Dagboektaak	Schrijf over een algemene activiteit.	n.v.t.
Sport toevoegen	Dagboektaak	Schrijf over een sportieve activiteit	n.v.t.

Voortgang

Het kind heeft na 2 weken het volgende uitgevoerd met betrekking tot het doel **Eten en Activiteit**:

Dag	Taak	Uitkomst	Totaal behaalde taken	Voortgang
1	Activiteit toevoegen	Afgerond	1	33,3%
13	Quizvraag over insuline spuiten en sporten	Onbeantwoord	1.5	50.0%
13	Quizvraag over insuline spuiten en sporten	Onbeantwoord	1.75	58,3%



In deze casus negeren we even de andere actieve doelen.

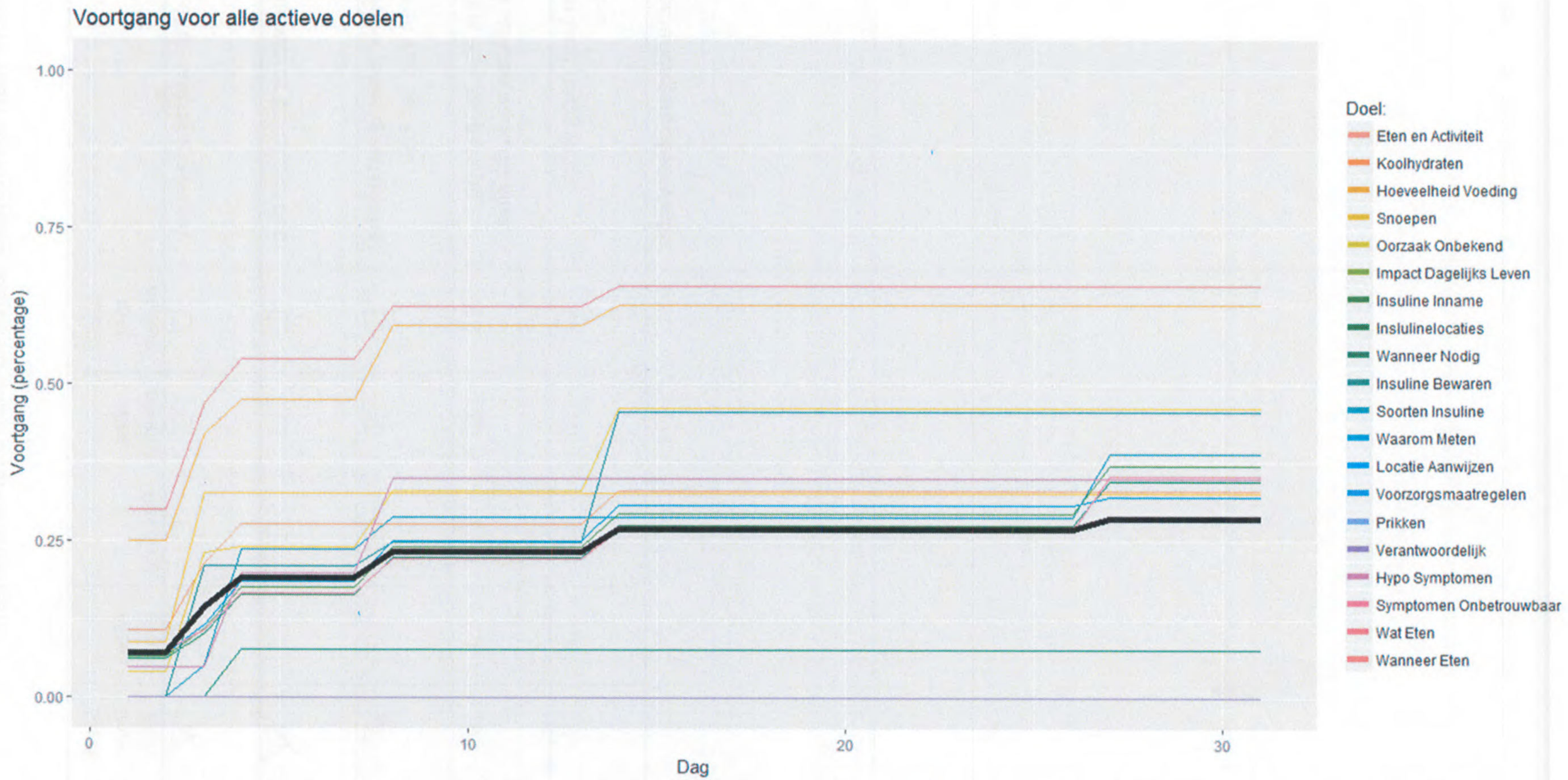
Kunt u op basis van (i) uw expertise, (ii) de kennis die u van het kind zou hebben buiten PAL om en (iii) de gegevens die PAL u toont zoals bovenstaand voorbeeld onderstaande stellingen beantwoorden?

	Sterk mee oneens	Mee oneens	Neutraal	Mee eens	Sterk mee eens
Het is voor mij duidelijk wat de voortgang is van het kind.	☐	☐	☐	☐	☒
Ik begrijp hoe de voortgang wordt berekend door PAL.	☐	☐	☐	☒	☐
Het is voor mij duidelijk wat ik moet doen om het kind maximaal te laten leren van het PAL systeem.	☐	☐	☐	☐	☒
Het is voor mij duidelijk of ik een aanpassing moet maken in de doelen selectie voor dit kind binnen PAL.	☐	☐	☐	☐	☒
Het is mij duidelijk wat het kind nodig heeft buiten het PAL systeem om.	☐	☐	☐	☐	☒
Eventueel aanvullende opmerkingen/observaties	weet natuurlijk niet hoe het er in mypall uit komt te zien / mogelijk uit komt te zien.				

Casus 2: Meerdere actieve doelen

Een kind heeft 20 actieve doelen. 1 maand na de eerste afspraak komt het kind langs bij u. Het PAL systeem laat u de volgende gegevens zien:

Doel	Voortgang
Eten en Activiteit	0%
Koolhydraten	33.0%
Hoeveelheid Voeding	62.5%
Snoepen	32,6%
Oorzaak Onbekend	46,1%
Impact Dagelijks Leven	0%
Insuline Inname	36,9%
Insulinelocaties	34,3%
Wanneer Nodig	7,7%
Insuline Bewaren	45,6%
Soorten Insuline	38,9%
Waarom Meten	32,1%
Locatie Aanwijzen	0%
Voorzorgsmaatregelen	0%
Prikken	0%
Hypo Symptomen	34,8%
Symptomen Onbetrouwbaar	35,2%
Wat Eten	65,6%
Wanneer Eten	65,6%


Voortgang voor alle actieve doelen
1.00
0.75
0.50
0.25
0.00
Voortgang (percentage)
0
10
20
30
Dag
Doel:
Eten en Activiteit
Koolhydraten
Hoeveelheid Voeding
Snoepen
Oorzaak Onbekend
Impact Dagelijks Leven
Insuline Inname
Inslulinelocaties
Wanneer Nodig
Insuline Bewaren
Soorten Insuline
Waarom Meten
Locatie Aanwijzen
Voorzorgsmaatregelen
Prikken
Verantwoordelijk
Hypo Symptomen
Symptomen Onbetrouwbaar
Wat Eten
Wanneer Eten

Kunt u op basis van (i) uw expertise, (ii) de kennis die u van het kind zou hebben buiten PAL om en (iii) de gegevens die PAL u toont zoals bovenstaand voorbeeld onderstaande stellingen beantwoorden?

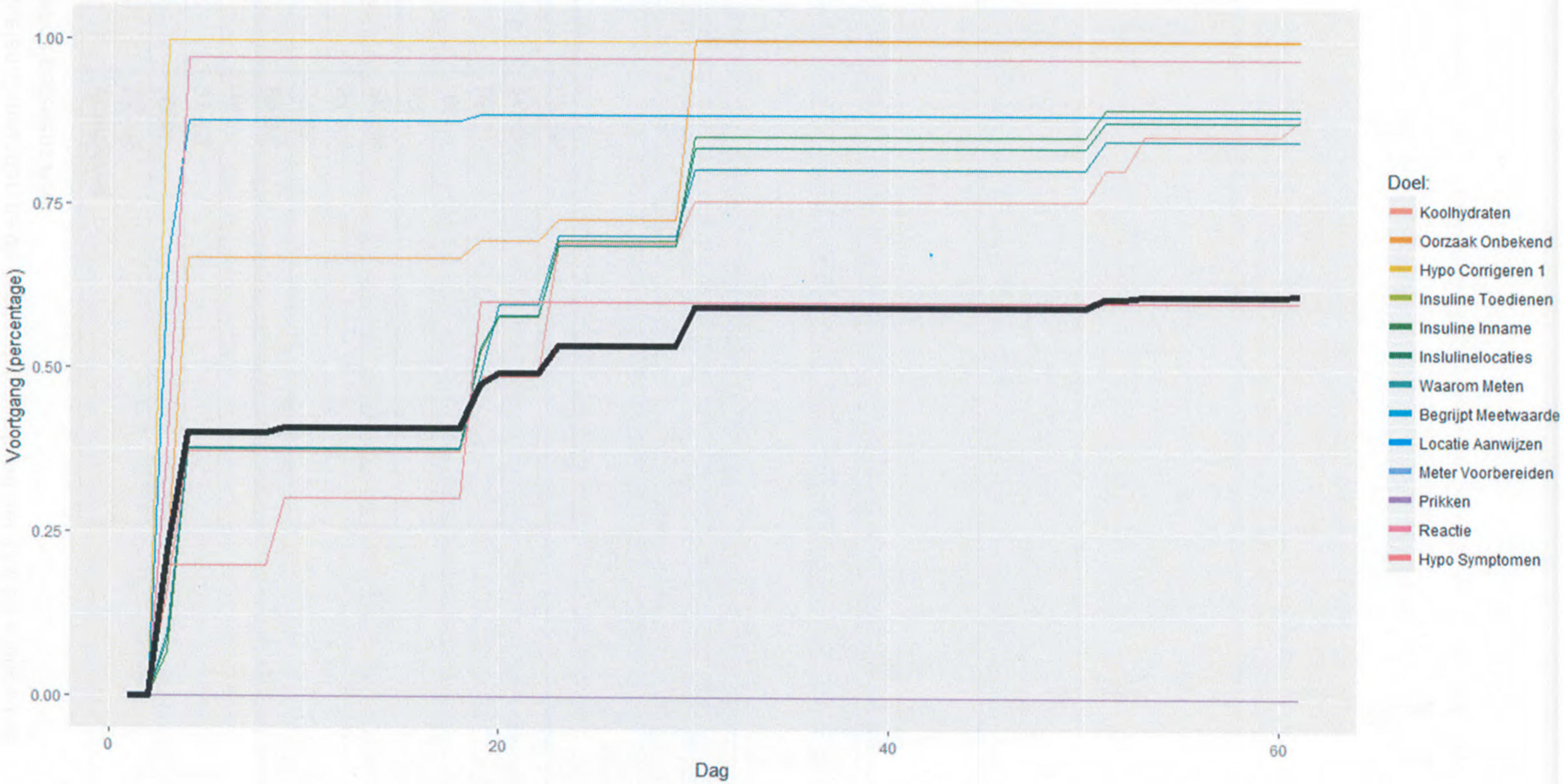
	Sterk mee oneens	Mee oneens	Neutraal	Mee eens	Sterk mee eens
Het is voor mij duidelijk wat de voortgang is van het kind.	☐	☐	☐	☐	☒
Ik begrijp hoe de voortgang wordt berekend door PAL.	☐	☐	☐	☐	☒
Het is voor mij duidelijk wat ik moet doen om het kind maximaal te laten leren van het PAL systeem.	☐	☐	☐	☐	☒
Het is voor mij duidelijk of ik een aanpassing moet maken in de doelen selectie voor dit kind binnen PAL.	☐	☐	☐	☐	☒
Het is mij duidelijk wat het kind nodig heeft buiten het PAL systeem om.	☐	☐	☐	☐	☒
Eventueel aanvullende opmerkingen/observaties					

Casus 3: Meerdere actieve doelen 2

Een kind heeft 12 actieve doelen. 2 maanden na de eerste afspraak komt het kind bij u langs. Het PAL systeem laat u de volgende gegevens zien:

Doel	**Voortgang**
Koolhydraten	88,0%
Oorzaak Onbekend	100%
Hypo Corrigeren 1	91,2%
Insuline Toedienen	0%
Insuline Inname	89,5%
Insulinelocaties	87,5%
Waarom Meten	84,7%
Begrijpt Meetwaarde	88,5%
Locatie Aanwijzen	0%
Meter Voorbereiden	0%
Prikken	0%
Reactie	76,6%
Hypo Symptomen	60,2%

Voortgang voor alle actieve doelen



Kunt u op basis van (i) uw expertise, (ii) de kennis die u van het kind zou hebben buiten PAL om en (iii) de gegevens die PAL u toont zoals bovenstaand voorbeeld onderstaande stellingen beantwoorden?

	Sterk mee oneens	Mee oneens	Neutraal	Mee eens	Sterk mee eens
Het is voor mij duidelijk wat de voortgang is van het kind.	☐	☐	☐	☐	☒
Ik begrijp hoe de voortgang wordt berekend door PAL.	☐	☐	☐	☐	☒
Het is voor mij duidelijk wat ik moet doen om het kind maximaal te laten leren van het PAL systeem.	☐	☐	☐	☐	☒
Het is voor mij duidelijk of ik een aanpassing moet maken in de doelen selectie voor dit kind binnen PAL.	☐	☐	☐	☐	☒
Het is mij duidelijk wat het kind nodig heeft buiten het PAL systeem om.	☐	☐	☐	☐	☒
Eventueel aanvullende opmerkingen/observaties					