Master's Thesis In Data Science : Dynamic Bayesian Networks supporting Self-Regulated Learning

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Abstract

This report aims at highlighting my work during the internship at the Brest University within the Lab-STICC laboratory, MOTEL Team. It took place between the beginning of February 2021 to the end of July 2021. Since we worked as a team, I will not consider being alone in the findings, thus I will now express myself as we. Then, we sums the existing literature regarding Self-Regulatory Learning in online environment and Dynamic Bayesian Networks. We also built a whole web based solution which handle the collection of traces and prompts on the France IOI's web platform : Quick-Pi. Finally, we show promising results using Dynamic Bayesian Networks and Data Analysis to support Self-Regulation Learning features.

Acknowledgements

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Thanks to the MOTEL Team, Lab'STICC, to introduce me to the work of researcher.

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Glossary

activity A set of **subjects**. 6, 33, 35, 36, 38, 39, 41, 42, 45–47, 53, 59, 61, 62

BN Bayesian Network. 23, 27, 28, 30, 47, 50, 52–54

connection An event representing the beginning of an **activity**. 41, 42, 59

DBN Dynamic Bayesian Network. 30, 47, 53–55

experimentation The event of self validating through step by step tool the proposed code. 41, 43, 44, 48–51

participant Someone which involves himself in an **activity**. 33, 37–44, 46–51, 53, 55, 59

participation The set of **connection** of a **participant** and an **activity**. 41, 59

SRL Self Regulated Learning. 6–16, 19–22, 28, 29, 31, 32, 57

subject An exercise proposed in different **versions**. 33, 34, 41–45, 47–51, 59

validation The event of validating the proposed code by the platform, with an affected score and error. 41, 43, 44, 48–51

version The difficulty of the exercise, version in 1,2,3,4. 34, 41–45, 47, 48, 51, 58

Contents

1 Introduction

In the latest context of Coronavirus and lockdown, students and professors faced new obstacles which forced them to use new ways of teaching and learning through the Internet. The rise of Massive Open Online Courses (MOOC) enabled education to continue through pandemic. However, those environments also raised new constraints. Some of the students have already the required skills to master their study, but others don't and may be heading to failure. Moreover, there is a growing need to understand and intervene in those environments [1]. That is why, researchers tend to focus on Self-Regulated Learning Theory (SRL) in order to find new ways of targeting students, who are giving up, and suggesting them accurate answers to help them persevere. SRL was firstly introduced as a psychology and educational sciences topic. However nowadays, this theory is also explored by computer scientists. In this master's thesis, we focused on the computer science field, using data science theory and concepts with regard to education. We decided to use Educational Data Mining (EDM) and Learning Analytics approaches (LA) [2], which deal with applying data mining and pattern mining methods to educational dataset in order to analyze how student engage in their learning process and report hidden insights.

Thus this internship is aimed at applying AI algorithm, regarding to SRL in an online environment. Learners should be classified by their behaviours and skills. Then, we want to suggest answers to help them improving in their own learning process and self-regulation skills. For this purpose, we use to work with FRANCE IOI, which is the largest french challenging computer science platform including challenges such as "Concours Castor", "Quick-pi", etc. In the first place, we collected and stored data by creating web services and modules regarding an activity on the Quick-Pi platform. Then studied data and created models which are able to correctly classify student's behaviours and SRL skills during the early period of a challenge.

Firstly, we go through SRL Theory and Artificial Intelligence algorithm State of the Art. Secondly, we highlight our work through data collection and storage. Then, we discuss about indicators and interesting findings in the data. Finally, we conclude with our models and results.

2 Self-Regulated Learning

In this section, we present a state of the art summary for the concepts of SRL.

2.1 SRL theory models

In order to begin, we have to introduce SRL models, whether they are the most referenced and accepted among researchers or because they show interesting aspects deeper than others do.

2.1.1 Zimmerman's approach

Zimmerman was one of the first to put words onto the definition of SRL, his approach was focused on the psychology part. According to him, the students who possess SRL skills can be defined as "metacognitively, motivationally and behaviorally participants in their own learning." [3]. The metacognitive processes are a group of skills such as planning, setting goals, self-monitoring, self-evaluating. While the motivation aspect takes care of interest in a task, self-efficacy and self-attributions. Finally, the behavior category is grouping : selecting, structuring and creating optimized environment for their own learning. Moreover, the self-regulatory feedback loop is also an important concept [4] : Learners should be able to both negatively and positively judge themselves regarding the outcomes and their goal. Last but not least, studying strategies is also a major concept : Learners may choose strategies over specific conditions and it is important to know why and how they did so, in order to reach their goal.

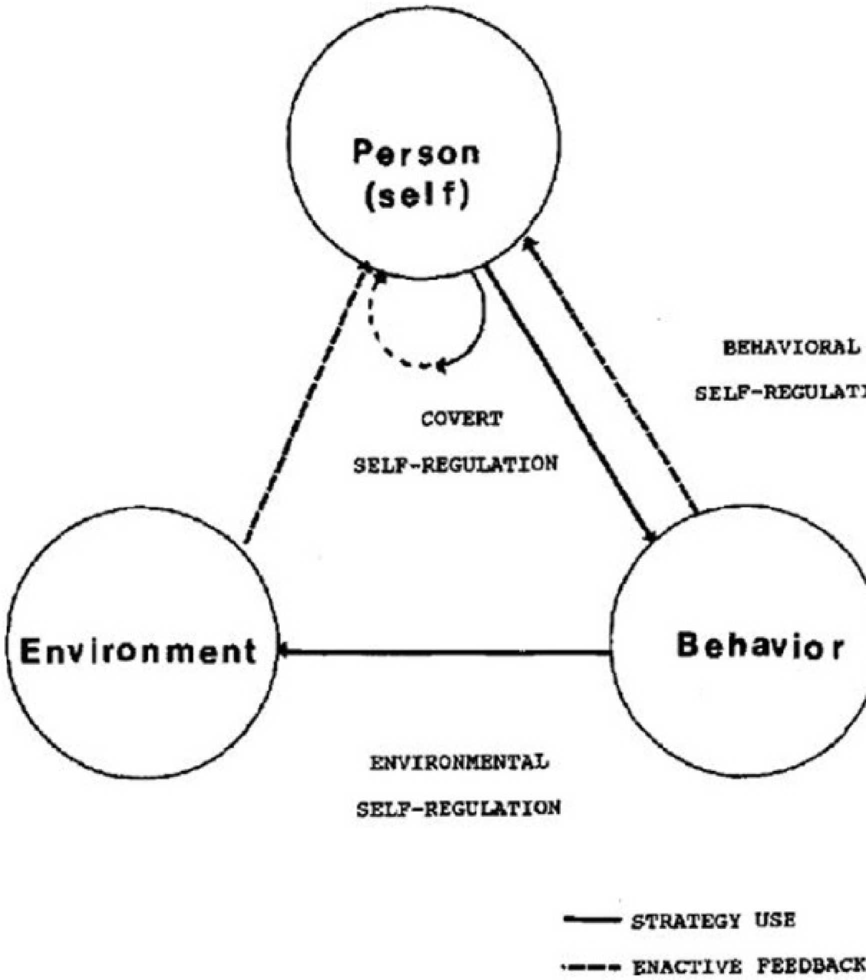

Figure 1: Triadic model of SRL from [4].

Regarding (Figure 1), we can see that nodes which represent important aspect of SRL are represented as a cycle rather than a path. The edges represent the importance of strategy use and feedback in the learning process such that : ones use a strategy which affect his behavior and environment. Then, this environment and behavior will send feedback to the learner regarding his action and the results, enabling him to reconsider his strategy. Each aspect can't be explained only by themselves but rather be considered as interdependent. By the time and with many other studies, Zimmerman was able to refine his initial loop by adding aspects and specific concepts to it (Figure 2). Firstly, students go over the forethought phase in which they have to be aware of their task, the outcomes they can get and finally the goals and strategies to follow in order to succeed.

Nextly, they have to work actively, by seeking help, being proactively participant in their own learning, creating a suitable studying environment etc. Then, they have to enter the self-reflection phase when it is time to judge whether or not their strategies, goals and satisfaction over the task is optimized or if they can do better. Finally, the cycle repeats even after the knowledge is acquired. Thus, we clearly see that reflection of ones learning is a really important part of the definition.

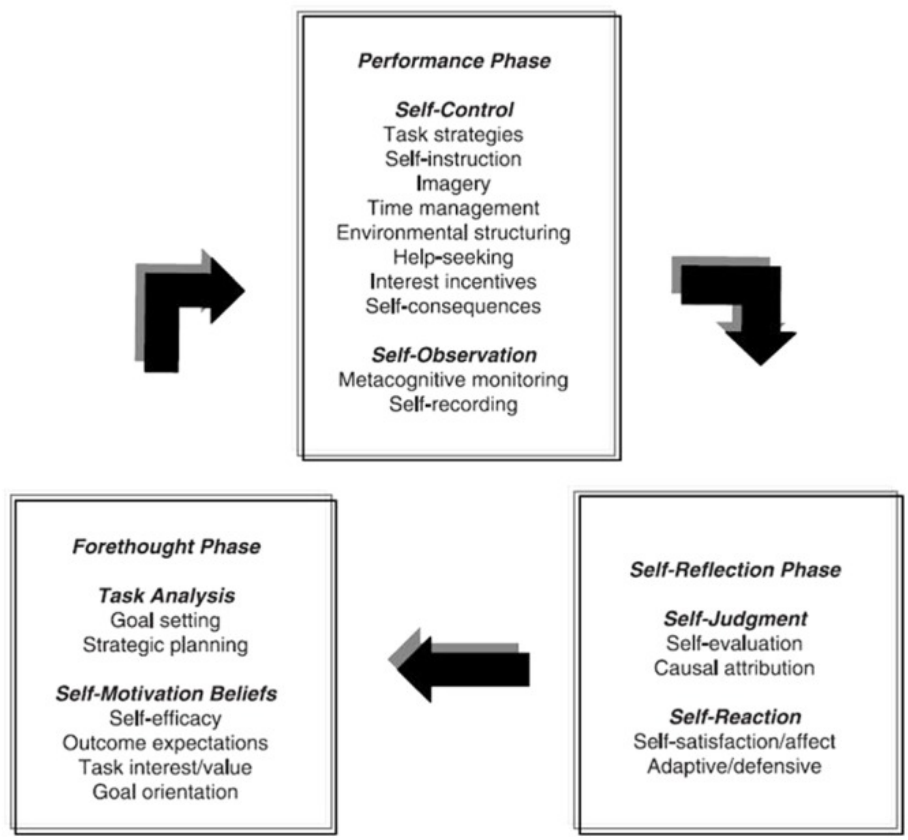

Figure 2: Cyclical phases model of SRL from [5].

2.1.2 Boekaerts' approach

As one of the first to conceptualize the concept of SRL, Boekaerts explored the theory in depth with a more clinical and emotional approach. She mainly focused on how feelings, emotion and motivation can drive the SRL pathway in the learning process. Firstly, she created a model which was mainly aimed at helping teachers and educational participants to understand concepts and create new educational tools to assess SRL [6]. As we can see on (Figure 3), there is still this idea of interdependent features such as Zimmerman stated. But this time, more than a loop, it can be considered as a path which the learners follows during the knowledge acquirement.

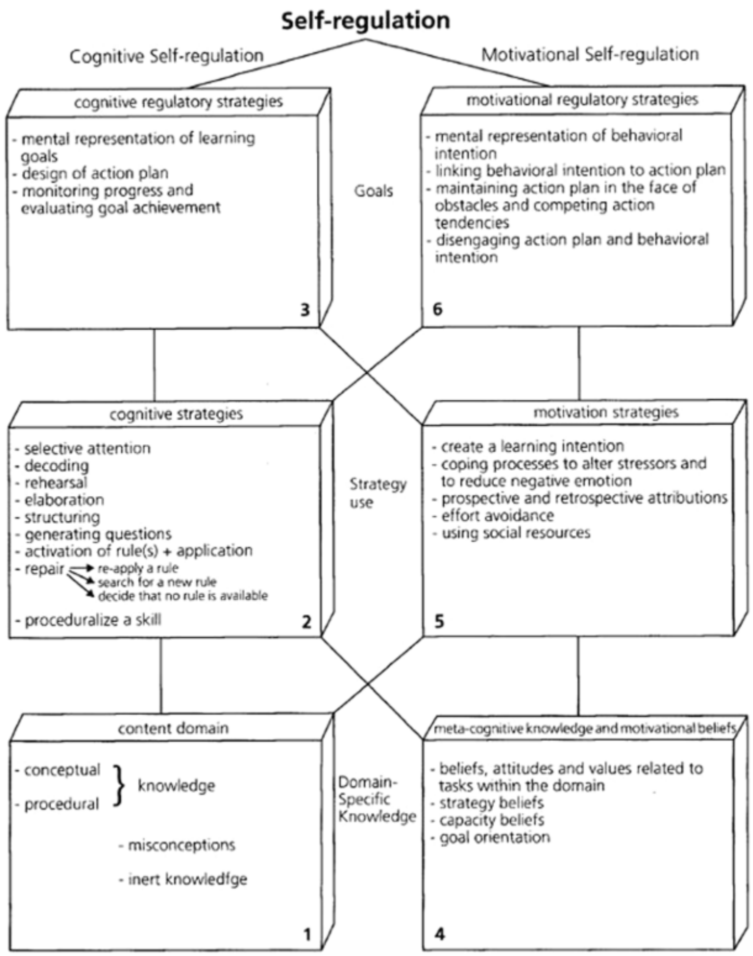

Figure 3: The six component of SRL from [7].

Nextly, she went even further in her research and proposed a new model called the Dual Processing SRL model. She defined two pathway : the mastery or growth pathway which tends to focus on task, goals to reach and needs. Then, the well-being pathway is defined as following emotions, personal motivation goals and protecting the self [6]. These pathways can be used in different approach : the Top-down approach focuses on the mastery/growth path in order to reach the mastery of a skill. The bottom-up approach is the action to move from the mastery path to the well-being path due to some sort of mismatch between the task and the self. The last approach is driven by social pressure, assessment (external) or self-consciousness pressure (internal) and will lead the learners to switch from well being path to the mastery path, (Figure 4). this approach helps to better understand the weight of emotion, motivation in the process of SRL.

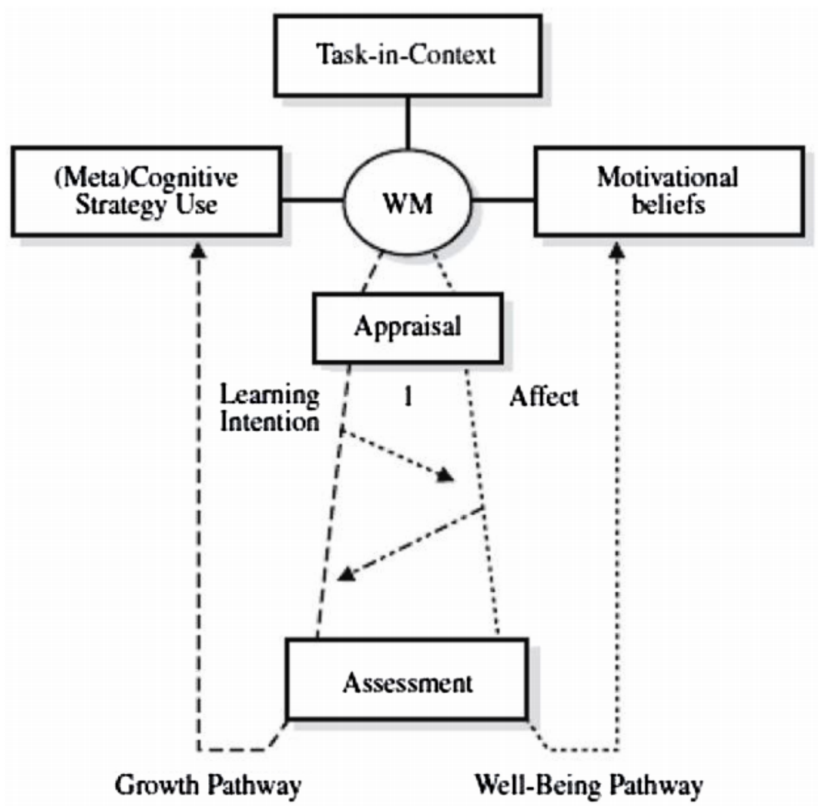

Figure 4: Dual Processing Model from [8].

2.1.3 Winne and Hadwin's approach

Winne and Hadwin developed a model which focus on the meta-cognitive aspects and the use of monitoring in the learning process. Moreover, it is one of the first to introduce the concept of a model which can be used on computers. They clearly explained how the student's cognitive planning, performing and evaluating tasks work. For this purpose, they defined four phases in which the learner goes and monitors himself regarding the task conditions or they cognitive conditions [6]. The definition of task represents the understanding of the objectives. Then, the learner enters in the planning and setting goals phase, where he will have to choose methods to validate objectives. Nextly, learners should conceptualize the action required to follow ones strategy and goals and finally, learners adapt themselves to conditions and will loop again over this process. Regarding (Figure 5), we can see that conditions are a main part of the learning process, they mainly influence how and why the learner take such path and monitoring through the learning process. The authors went in depth into each conditions, providing a really complete understanding of them.

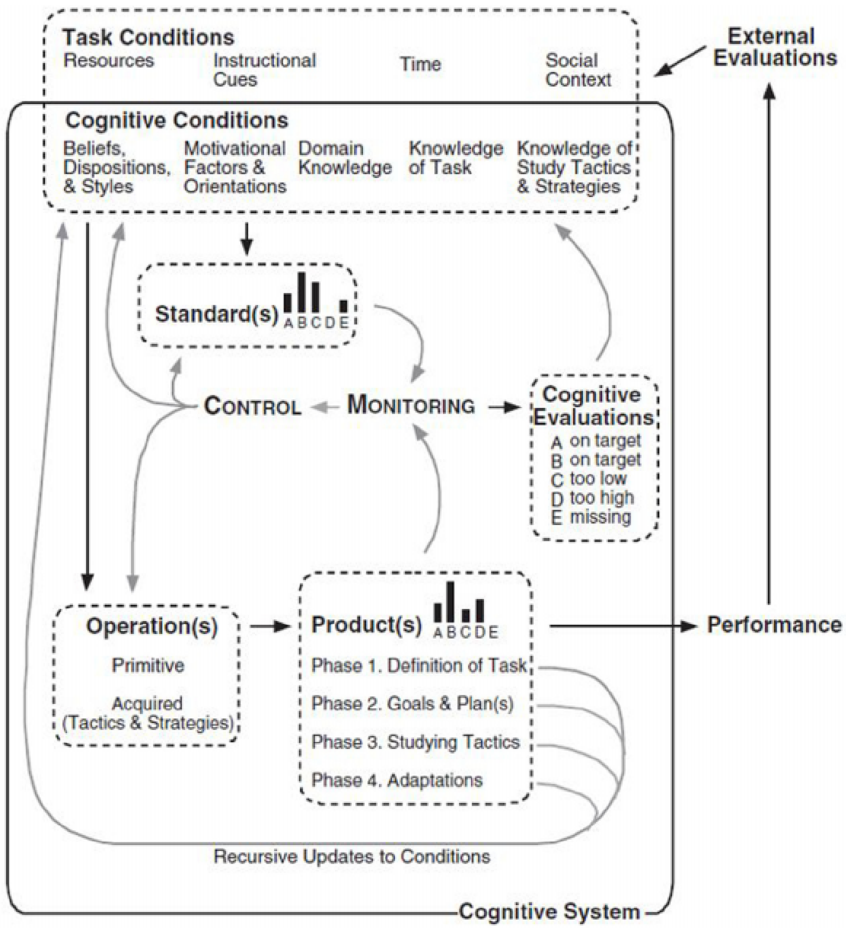

Figure 5: Winne's SRL model from [9].

However, this model barely takes into account emotions and motivations factors, which were proven to be a main part of SRL.

2.1.4 Pintrinch's approach

Pintrinch's model is one of the most accepted one towards research community. His work focused on the relation between SRL and motivation, but what makes it so popular is the Motivated Strategies for Learning Questionnaire (MLSQ). In order to better understand this questionnaire, we detail the model and then jump into it. Firstly, the author defined 4 phases which represent all the known aspects of the SRL : the forethought phase which aim at setting goals, strategies, understanding tasks, etc. The monitoring phase which deals about the use of monitoring through motivation, emotions, tasks and context conditions. Then, the control phase which aims at choosing, selecting actions and adaptations in order to reach/abandon ones goals following ones strategies. And finally, the reaction and reflection phase which deals with learners handling of emotions, judgement over their actions and self positioning in the task [6]. As we can see in (Figure 6), these phases use several features such as cognition, motivation and affects, behavior and finally context principles. This follows the fact each feature acts with another and can't be explained alone.

	Areas for regulation			
Phases	Cognition	Motivation/affect	Behavior	Context
1. Forethought, planning, and activation	Target goal setting	Goal orientation adoption	[Time and effort planning]	[Perceptions of task]
	Prior content knowledge activation	Efficacy judgments	[Planning for self-observations of behavior]	[Perceptions of context]
	Metacognitive knowledge activation	Ease of learning judgements (EOLs); perceptions of task difficulty		
		Task value activation		
		Interest activation		
2. Monitoring	Metacognitive awareness and monitoring of cognition (FOKs, JOLs)	Awareness and monitoring of motivation and affect	Awareness and monitoring of effort, time use, need for help	Monitoring changing task and context conditions
			Self-observation of behavior	
3. Control	Selection and adaptation of cognitive strategies for learning, thinking	Selection and adaptation of strategies for managing motivation and affect	Increase/decrease effort	Change or renegotiate task
			Persist, give up	Change or leave context
			Help-seeking behavior	
4. Reaction and reflection	Cognitive judgments	Affective reactions	Choice behavior	Evaluation of task
	Attributions	Attributions		Evaluation of context

Figure 6: Pintrinch's SRL model from [10].

Thus, the MLSQ questionnaire [11] based himself on the previous model. It brings information over strategies, motivation, context and several other features. Every features follows a 5-Likert scales indicating the confidence in the answer. The author provided two version both for high school and college students, but one criticism done to this questionnaire is that it is not proved to work on computer based environments.

2.1.5 Synthesis on SRL models

In this subsection, we sums up the contributions and the criticisms in the literature, done to the authors regarding their SRL model.

Model	Focus On	Contribution	Lack
Zimmerman	Psychology Self-Reflection	Interdependency of SRL features. SRL Feedback loop.	Not adapted to digital environment
Boekaerts	Psychology Clinical and Emotional	Balance between well-being and learning pathways.	Monitoring and feedbacks less taken into account
Winne and Hadwin	Psychology Metacognition and Monitoring	Process of Monitoring through strategy, evaluation of self and conditions. Task and Cognitive conditions influencing meta-cognition processes.	Motivation aspect barely taken into account
Pintrinch	Psychology Motivation	Impact of Motivation in each SRL phase. Clearly defined area of regulation through phases.	There are no clear interactions or relations between each phases or areas

Table 1: SRL models' contribution

2.2 Digital environments supporting SRL

In this section, we discuss the benefits and risks of using SRL in the context of measuring or assessing learners on digital environment.

The major advantage of the SRL is that the student is now the main monitor of his own learning rather than the teacher. Then, it perfectly fits the new web platforms aimed at the education. Nevertheless, Young [12] ran an experience which shows that inequalities between learners increase in a environment that supports SRL. He ran an experiment with the aim to find in which environment the difference between high SRL and low SRL was the higher, and if the difference between the two learning environment made performing high SRL students better. Thus, He conducted a course on an online support where students were randomly affected a CBI environment (Computer-Based Instruction, or also PC : Program Control), and a LC environment (Learners Control). In the first case, student had no choice to follow the given course in the order chosen by the author. In the second case, they could choose which concept to learn at which time they want. They can review or not some course when they wanted to. Thus, he classified each of the student regarding their SRL skills (low or high). He found that, regarding CBI environment, students were quite equal in the results (low : 67.7%, high : 64.7% validation score). However, in the environment that supports SRL, it seems that high SRL students performs better (73.2%) but low SRL students seems to be totally lost (37.0%). Thus, it shows environment that supports SRL can lead to better results but require learners to have specific set of skills that were not really required before. However this experiment was only done on 26 students, meaning that we should be aware of potential statistics inaccuracy.

Moreover, Pressley [13] also found that teaching self-regulation mechanics is harder than the common thinking. Adults are able to experiments by themselves and choose the best strategy regarding their experimentation whether or not a recommendation is done by a third party, whereas children seem to be more confused by the combination of experiences and recommendation. They keep relying on both, even if they clearly had the opportunity to see the effectiveness of one method rather than another. Then, it highlights the fact that children need to have some kind of clear path to follow rather than a total liberty of action.

Surprisingly, Kornell [14] shows that, suggesting action is also a complicated and misleading path. Learners were offered the right to obfuscate words from their learning tasks to focus on the others, expecting them to fully understand those tasks. But the result shows the contrary, learners without any possibilities were doing better on the final evaluation. In addition, advising user to run several experiments in order to learn by themselves can also be counterproductive. In fact, the more a learner struggled by experimenting and if he succeed at the end, the more efficient is the learning process. Contrariwise, if they didn't succeed, it amplifies the waste of time management and ineffectiveness of the learning method.

Therefore, these statements show that we can't consider SRL as a perfect learning environment by itself. In fact, it requires exterior mechanics to help the lowest SRL students, but those mechanics should be also proven not to be counterproductive.

2.3 SRL Measurement

Regarding SRL theory, assessing SRL skills is rather a complicated task. In this subsection, we show the motivation of why and how to assess SRL on a computer based environment.

2.3.1 Questionnaires

Questionnaires are great tools in scientific literature which help to measure each of the many features of SRL. They are the most approved and used tool. In this context, we focus on one of the most interesting ones for online learning : the Self-Regulated Online Learning Questionnaire : **SOL-Q**.

Plenty of researchers have already proposed ways to address questionnaires in order to assess SRL skills. Yet, as Jansen [15] stated, it only exists few which are proven for an online environment. Moreover, during the refining of SRL models, questionnaires felt like they miss some aspects of the new models or focus on specific aspect of SRL. In order to show this previous statement, the authors based themselves on the Puustinen's [16] article and model (Figure 7). This model is highly related to previous models that we explained in 2.1, the way we may measure SRL is more or less near to the theoretical models. For example, we find the preparatory phase corresponding to the forethought and planning phase. They proposed three main phases including Preparatory Phase : where the learner understands the task, tries to plan, sets goals and strategies to reach them. Then, the performance phase where the learner manages his environment, time and be proactively part of his own learning by seeking help, being motivated, etc. Finally, the learner arrives at the Appraisal phase where he has to think about his strategies, goals and progress in order to adapt himself.

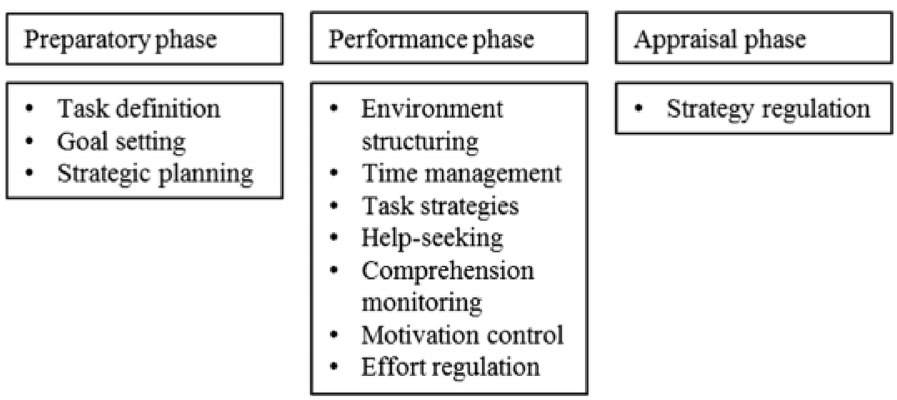

Figure 7: Puustinen's SRL models from [16]

In addition, Jansen proposed to study the four more used questionnaires in the literature including **MSLQ** : Motivated Strategies for Learning Questionnaire [17], **OSLQ** : Online Self-regulated Learning Questionnaire [18], **MAI** : Metacognitive Awareness Inventory [19] and **LS** : Learning Strategies [20] (Figure 8). Then, he proposed a new questionnaire : the **SOL-Q**, validated for the online usage and which takes into account every aspect of the SRL while being the more concise as possible.

	MSLQ	MAI	OSLQ	LS
Preparatory phase				
Task definition		X		
Goal setting		X	X	
Strategic planning		X		
Performance phase				
Environmental structuring	X		X	
Time management	X		X	
Task strategies	X	X	X	X
Help-seeking	X		X	X
Comprehension monitoring		X	X	X
Motivation control				X
Effort regulation	X			
Apprasial phase				
Strategy regulation		X		

Figure 8: Scales of each questionnaires from [15]

In this paper, the authors used a two time proof for their questionnaire. Firstly, they regrouped every items of each questionnaires in the previous categories (concatenating overlapping questions, trying to regroup similar ones) and obtained a model with 53 questions. Then, they proposed several new questionnaires based on several methods. We will only focus on the Exploratory Factor Analysis, which aimed at selecting the most important factors from the model. Rather than using Kaiser criterion, they chose to use data matrices which leads them to less controversial results. Finally, they obtained a new model with 36 items and which imposes to refactor the previous categories (Figure 9). For example, the authors showed that metacognitive skills shouldn't be separated in several categories.

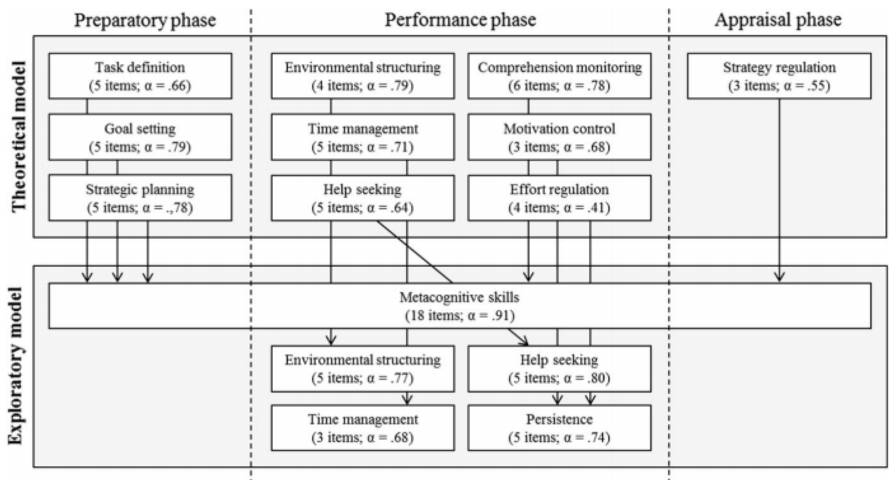

Figure 9: EFA result questionnaire from [15]

Nextly, they ran a second experiment using Confirmatory Factor Analysis. For this purpose, they collected 159 students' questionnaire over a Dutch and English MOOC using their 4 models (including theoretical model and exploratory model that we already speak about). Each question had to be answered with a 7-Likert scales indicating the confidence or not regarding the question asked. By using several indicators, both relative and absolute fit indices, they were able to obtain relevant results which show that the Exploratory model obtained with the EFA has greater fitting scores (Figure 10). Lastly, following these results, they proposed the SOL-Q questionnaire composed of 36 items dispatched in 5 categories. We won't list them here since the Jansen's paper do it already with great precision in its appendix.

Statistic	Theoretical model with task strategies	Theoretical model without task strategies	Exploratory model	Exploratory-theoretical model
χ^2	2530 (p = .000; df = 1270)	1782 (p = .000; df = 900)	1066 (p = .000; df = 584)	1119 (p = .000; df = 573)
NC	1.99	1.98	1.83	1.95
RMSEA	.081 (.076–.085)	.080 (.075–.086)	.074 (.067–.081)	.079 (.072–.086)
CFI	.666	.705	.777	.747
AIC	2852	2052	1230	1305

Figure 10: CFA result questionnaire from [15]

While this paper highlights several interesting concepts, such as categories of questions, concise and online adapted questionnaire, it targets older people (the mean age for this questionnaire was near 44 years old). In our context, going from French Elementary school, Middle and High school, the questions can feel a little bit confusing and too hard to be understandable by the children/teenagers. Moreover, authors correctly highlighted the fact that MOOCs are special environments where rules totally change. For example, while in a class context it was assumed that the preparatory phase would be assumed by the teacher, in MOOCs, it is rather the student which will assume this role. Regarding the previous problem of rating SRL skills of children without having any teaching context, it can make our process more complex.

2.3.2 Prompts

Prompts are a main part of SRL assessment when it comes to computer based platform. They are often represented as pop-ups which appear at a specific time during the learning process in order to ask question regarding SRL features to the learner. They allow to collect data before, during and after the exercises. Thus, they enable to add important data for an In-Real Time predictions of SRL and then a response to help the learner which may be detected to be in great difficulties. It also gives crucial information of how the learner is evolving in his environment [21].

In Sabourin's paper [22], the authors built a simulation detective game with the aim of assessing SRL on a computer platform. For this purpose, participants were offered several options to use in context without much information. Their final aim was defined clearly, but they had to conduct by their own an investigation, discover the environment and run experiences. Participant had 55 minutes to end the game. In the first place, they established a pre-profile of the student related to a questionnaire, regarding some aspect of SRL. Then, they collected data with in-real time prompts during the game about motivations and other evolving factors. Thanks to these prompt, they were able to better predict the category of SRL of each student. As (Figure 11) shows, the authors used the models at several different timers to estimate the best prediction AI models can score. The reports' tags correspond to the SRL in-real time prompts done at 4,11,18 minutes of the game and some trace collected along the participant actions. These scores show that prompts can make the difference in better predicting the SRL category of students.

Model	Predictive Accuracy				Low-SRL Recall			
	Initial	Report$_1$	Report$_2$	Report$_3$	Initial	Report$_1$	Report$_2$	Report$_3$
Naïve Bayes	44.2	43.5	46.1*	50.5*	0.47	0.28	0.54	0.52
Neural Network	42.3	43.8	46.5*	45.5	0.44	0.45	0.49	0.52
Log. Reg.	42.7	51.2**	47.7	54.5**	0.45	0.65	0.66	0.73
SVM	43.5	46.9*	45.7	51.4**	0.51	0.55	0.56	0.62
Decision Tree	42.7	46.2*	48.1*	57.2**	0.45	0.55	0.71	0.71

Figure 11: AI model prediction result [22]

Moreover, Wong [23] collected several studies which show that prompting participants will enable them to overcome some of their difficulties and may lead them to the path of a better self regulation. Firstly, prompting student may increase their planning ability, goal setting [21] and accuracy of seeking information through a free environment [24]. Moreover, learners prompted which were classified as low students SRL can improve themselves due to prompt and become high students SRL, which are able of the same monitoring mechanisms than better students [25]. However, one important aspect that Wong highlights, is that prompting is way more effective on learners who had the opportunity to understand it before using it, or having prior knowledge to it.

2.3.3 Interaction Traces

Trace or Log Event are a type of data which contains a timestamp, a link to what it is related and an known event with parameters.

As already mentioned before, stealth methods should be considered as one of the most important part for assessing SRL. Since prompting questionnaires create bias within students behaviors, researchers have though of better ways to collect data and keep student as if they were acting in real conditions. Trace data have been highlighted by several article such as [26] and [27] to better fit the behavior of learners than traditional statistics (mean, median, etc.) [28].

Researchers show that relying on frequency-based statistical analysis doesn't take into account the dimension and time-evolving nature of the SRL features [28]. Moreover, these models consider a group of learners and try to compare their indicators to the individual behavior of a learner. This is not accurate since each individual as his own way of learning and should not refer to the average but to an other category of learner. Whereas, studying data in the perspective of time-series with sequential and temporal pattern mining lead to better understanding of the nature of SRL [26].

Several ways have been explored following this statement, but the most promising ones comes from the Siadaty's article [29] which was one of the first to conceptualize Micro and Macro processing of SRL regarding Trace data. In this article, the authors proposed a model of SRL (Figure 12) where each of the collected data appears in the form of a Trace/Event Log (Figure 13). Due to their nature, events alone doesn't indicate much to SRL features, but it is rather the combination of series of events which are rather interesting. Then, the aim behind this process is to apply sequential and temporal analysis in order to find recurrent sequences of events which can be then representative of micro-level srl processes (srl features).

Table 1: Micro-level processes included in the SRL model and their descriptions (Siadaty, Gašević, et al., 2012).

Macro-level SRL process	Micro-level SRL process	Description
Planning	Task Analysis	To get familiar with the learning context and the definition and requirements of a (learning) task at hand
	Goal Setting	To explicitly set, define, or update learning goals
	Making Personal Plans	To create plans and select strategies for achieving a set learning goal
Engagement	Working on the Task	To consistently engage with a learning task, using tactics and strategies
	Applying Strategy Changes	To revise learning strategies, or apply a change in tactics
Evaluation & Reflection	Evaluation	Evaluating one's learning process and comparing one's work with the goal
	Applying Strategy Changes	Reflecting on individual learning and sharing learning experiences

Figure 12: Siadati's SRL model [29]

userEvalUserNo	eventTime	eventId	eventType	propKey	propValue	resourceType	resourceURI
LA77	2012-0...	17684	SelectNodeEvent	nodeView	target	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17684	SelectNodeEvent	nodeid	1.1.3.1.2...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17685	OpenTabEvent	tabName	Asset For...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17685	OpenTabEvent	nodeTitle	Referenc...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17685	OpenTabEvent	nodeRelName	ASSET	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17685	OpenTabEvent	nodeView	target	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17685	OpenTabEvent	serviceName	LPC	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17685	OpenTabEvent	nodeid	1.1.3.1.2...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17686	TaggingEvent	keywords	website	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17687	Edit	keywords	website	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17687	Edit	visibility	Public	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17687	Edit	assetURL	/reference/	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17688	SelectNodeEvent	nodeTitle	The C Pro...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17688	SelectNodeEvent	nodeRelName	ASSET	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17688	SelectNodeEvent	nodeView	target	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17688	SelectNodeEvent	nodeid	1.1.3.1.5...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17689	OpenTabEvent	tabName	Asset For...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17689	OpenTabEvent	nodeTitle	The C Pro...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17689	OpenTabEvent	nodeRelName	ASSET	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17689	OpenTabEvent	nodeView	target	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17689	OpenTabEvent	serviceName	LPC	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0...	17689	OpenTabEvent	nodeid	1.1.3.1.5...	KnowledgeAsset	http://intelleo.org/triplestore/bc_x#KnowledgeAsse...
LA77	2012-0	17690	SelectNodeEvent	nodeTitle	[illegible]	Activity	[illegible]

Figure 13: Trace Event example [29]

Even if this process is still promising and currently a research trend, it should be noticed that there are also limitations due to its newness. One the main criticism is that there are still no framework well accepted and theory is currently evolving in the field. Moreover, considering data as Event doesn't take into account the interdependency of each SRL features with another.

2.3.4 A synthesis of SRL measurement

Measure	Data type	Benefits	drawbacks
Question-naire	Ordinal (Likert)	Complete SRL Features measured. Researcher's approval. Ready to use	Time-consuming. Hardly understandable by under the age of majority learners. Not always adapted to digital usages. Assessment is not stealth.
Prompts	Ordinal (Likert) or Categorical (choices)	Adaptive Time and Understanding. Adapted to digital environment	Need to prove efficiency and readability of each question. Assessment is not stealth.
Trace	Log (Timestamp, event, information)	Stealth assessment. Report real actions rather than one's thinking. Can display hidden potential SRL features. Adapted to digital environment	Actions alone doesn't mean anything (for example : a click). Data needs to be related to the context of the platform. Hard to aggregate data to find real indicators

Table 2: SRL Measure Types' contribution

3 Bayesian Networks : Theoretical frame and algorithms

In this section, we introduce the main Artificial Intelligence algorithms and theories which help us to understand and categorize learners in online environment.

3.1 An introduction to Bayesian Networks

Bayesian Networks (BN) are part of the probabilistic theory and graphical model. They represent a joint distribution which is aimed to be simplified by the use of independency between variables[30]. They are often represented as a directed acyclic graph (DAG), with nodes representing the variables and the directed edge the dependency between one variable to an other. In (Figure 14), we note Weather as the parent of IsMotivated and IsMotivated as the child of Weather and so on for each node and directed edge.

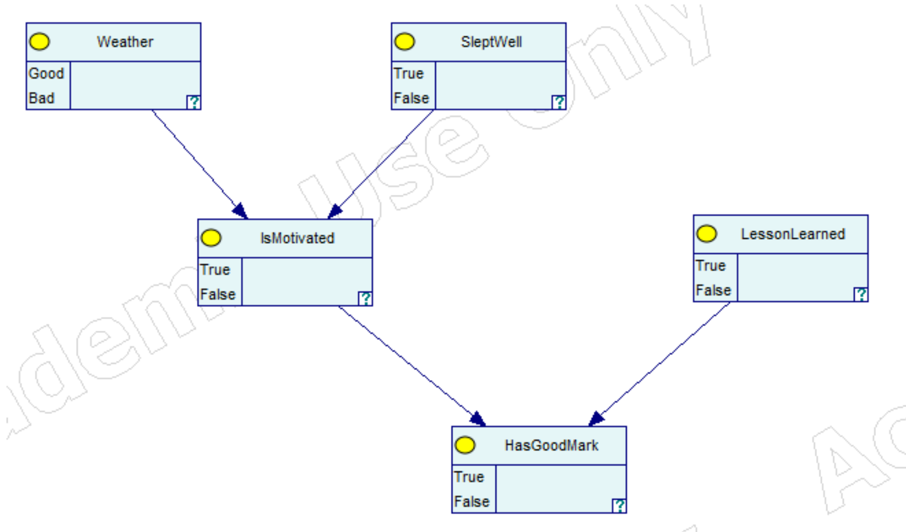

Figure 14: DAG representing a BN using GeNIe Modeler

Bayesian Networks use the Markov assumption which assume that considering a set of variable, each variable will be only dependent with its parents and child. Therefore, it helps to simplify the joint distribution of a set of variables and enables to consider the related node as independent of the past variables and only dependent of their parent variables. Then, each node or variable is expressed as a conditional probability of all its parents. In a set of a binary variables, regarding (Figure 14), the Weather variable would have 2 conditional probabilities to store and the IsMotivated variable $4 * 2 = 8$. This comes from the formula $2^m * n$ with m the number of parent of the node and n the number of state of the variable. Thus, simplifying the network with independencies can be really a gain over the complexity problem, but it assumes that every variables can be totally independent with another which is rarely the case in real problems. The way to handle this problem is to only consider a sufficient amount of the best dependent variables. The more we add variables and edges, the more it is supposed to be near from reality. Last but not least, BNs are really useful model to understand the relation between variables, as they provide easily readable graphical representation and interaction. So they can be built from data or/and expert in the field.

3.2 Belief Propagation

When the networks is complete with all Conditional Probability Dependencies (CPDs), we can make several observations regarding only some of the variables. Regarding (Figure 15), the variable IsMotivated is observed to True. This totally changes each probability for each nodes since we are sure that IsMotivated is set to true. Thus, the belief propagation is aimed at updating all the network regarding every observed nodes. One of the main algorithm for this task is the Message Passing Algorithm [31].

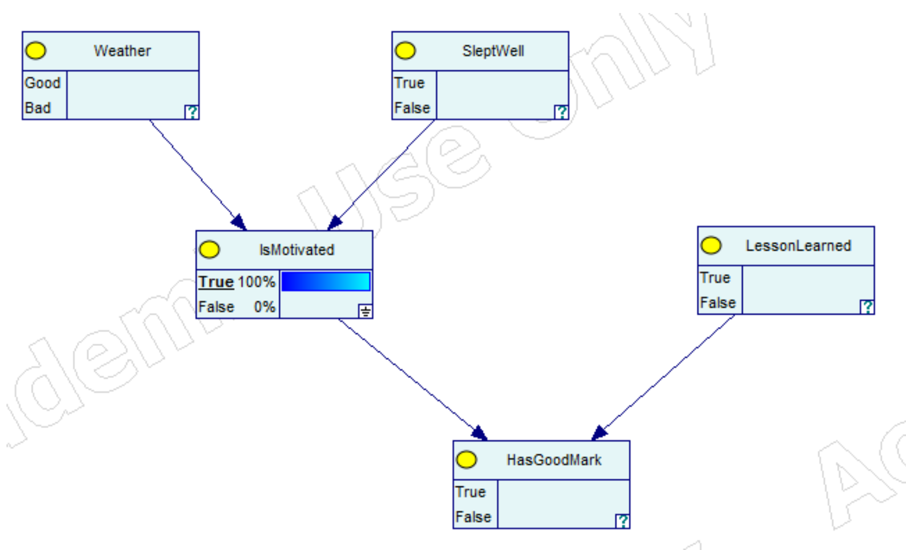

Figure 15: Bayesian Network with observed node

In order to update each variables, we will create two messages, one from the parents of the node and ascendant of parents to the node. Another from the children of the node and descendent of children of the node. Each message coming to the node will be used with CPDs to compute the marginal probabilities of the node [30]. In (Figure 16), after applying the message passing algorithm, each state of each node obtain a new marginal probability regarding observed nodes. This is helpful to understand relations between variables in our network, it makes the Bayesian Networks a powerful tool to understand interactions with variables in a dataset.

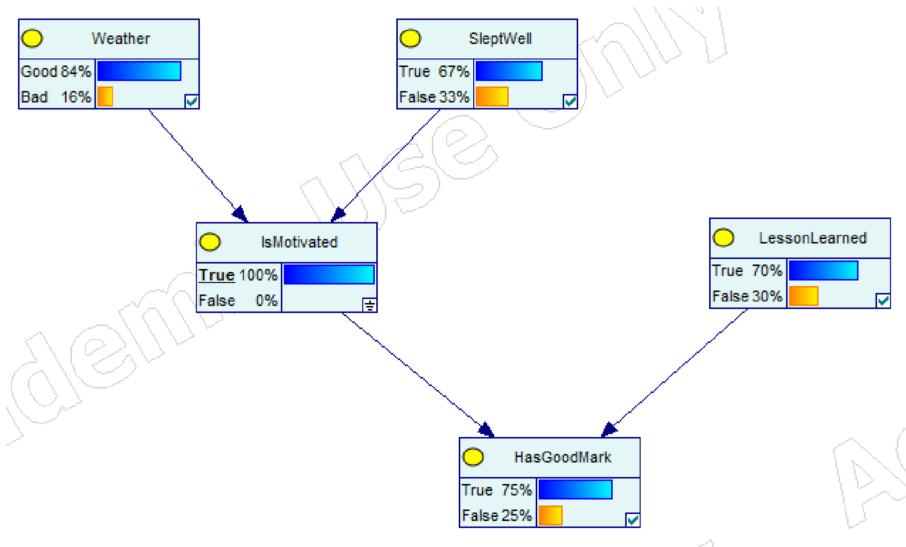

Figure 16: Bayesian Network with observed node and belief propagated

3.3 Parameter Learning

As we already mentioned it before, the CPDs can be built with both expert knowledge but also datasets. When an expert is not available or that we have some confidence in our dataset, we can try to estimate our CPDs using the parameter learning's algorithm. It is obvious that, the more data we have in our dataset, the more the estimation will be robust. There are two cases : when the dataset has complete data and incomplete data.

3.3.1 Complete Data

In the case of complete Data, it exists several algorithm but we will focus only on Maximum Likelihood Estimation (MLE) and Expection A Posteriori (EAP). Regarding MLE[32], the aim is to estimate each state of parameter θ (conditional probabilities) :

$$\hat{P}(X_i = x_k | Pa(X_i) = x_j) = \theta^{MLE}_{i,j,k} = \frac{N_{i,j,k}}{\sum_k N_{i,j,k}} \quad (1)$$

with $N_{i,j,k}$ the number of occurrences of $X_i = x_k$ and $Pa(X_i) = x_k$. And $Pa(X_i)$ the parent CPD state regarding X_i.
Regarding **Table 1**, we obtain :

- $P(V1 = a) = \frac{4}{4+3} = \frac{4}{7}$
- $P(V1 = b) = \frac{3}{7}$

- $P(V2 = a|V1 = a) = \frac{3}{4}$
- $P(V2 = b|V1 = a) = \frac{1}{4}$

One of the major problem of MLE is that it requires a certain amount of data to be statistically confident. If our data are not sufficient and biased regarding the reality, there will be not adjustment or regulation over the likelihood computation and thus it can lead to really biased CPDs.

Therefore, we consider using the EAP algorithm which use Dirichlet coefficient to regulate the likelihood [33]. we compute :

$$\hat{P}(X_i = x_k|Pa(X_i) = x_j) = \theta^{EAP}_{i,j,k} = \frac{N_{i,j,k} + \alpha_{i,j,k}}{\sum_k (N_{i,j,k} + \alpha_{i,j,k})} \tag{2}$$

with $\alpha_{i,j,k}$ a Dirichlet coefficient. We define the Dirichlet coefficient :

- α of $P(V1) = [50, 50]$
- α of $P(V2|V1 = a) = [90, 10]$

with index corresponding to letters in the alphabetic order. Regarding **Table 1**, we obtain :

- $P(V1 = a) = \frac{4+50}{4+3+100} = \frac{54}{107}$
- $P(V1 = b) = \frac{53}{107}$
- $P(V2 = a|V1 = a) = \frac{93}{104}$
- $P(V2 = b|V1 = a) = \frac{11}{104}$

Here, the fraction are more balanced regarding the Dirichlet coefficient. But the more data with have in our dataset, the less those coefficients will have some weight in the computation.

V1	V2
a	a
a	b
b	b
a	a
a	a
b	b
b	a

Table 3: Small example Dataset for complete Parameter Learning

3.3.2 Incomplete Data

In some cases, our dataset can lack some values in observed or collected variables. It may be a problem since, regarding complete data analysis, we would have to eliminate each of the row which contains at least 1 missing value. Then, it will bias our model and result. But in those rows, there are still interesting values, which can be used to improve some of the conditional probabilities.

In this part, we will mainly focus on the Expectation Maximization algorithm (EM), which one of the most known and accepted through researchers. But we can use several other methods such as Gibbs Sampling, RBE Algorithm or data perturbation [34]. This algorithm proceeds with several steps : In the initialisation process, we estimate the conditional probabilities of the network based on several methods (Random, Complete Data analysis, Constrained EM, ...). Then, we can enter in the Expectation phase were we will loop for the first time over the dataset, taking each row one by one, considering only the one with missing values. By using inference with each row, we are able to obtain new count values for missing values and then, each missing values will have as many probability than the number of categories it has, such that each category has a probability regarding inference of the row. Therefore, we can use those probabilities on each row to increase our contingency table and thus update the parameters (conditional probabilities), this is the Maximization phase. Since our model is more reliable by the end of the previous process, researchers have shown that repeating the process until the parameters converges will lead to better estimations [35].

However, the EM algorithm is still subject to criticism. In the context of important missing values, it may performs poorer than expected and lead to biased results [34], researchers proposed the CEM algorithm with tends to improve this process. Moreover, EM found itself easily stuck in local minimum rather than global minimum without the possibility to get out, researchers [36] also found a way to improve such results.

3.4 Dynamic Bayesian Network

Dynamic Bayesian Network concept lies between probabilistic graphical model and the Markov Theory. They are often used to represent complex BNs with a discrete time parameter. It means that a set of variable X exists at several fixed time intervals and repeats itself such that $X = \{X_1, ..., X_t\}$ with t the discrete time. Such set of variables has inner-dependencies, meaning that all the variables in X_1 are dependent or not to other variables in X_1, and external dependencies such that, X_1 variables are dependent or not to X_2 variables and so on [37]. An example is shown in (Figure 17), where we represented the simplified human process of eating. In DBNs, the current time set of variable is said to be only dependent of its past nodes. Each past variable can interact with a future variable which is may not be in the next set but in the n-th set, these relations are said to be order n. In (Figure 17), there are only first-order relation between past and current variables.

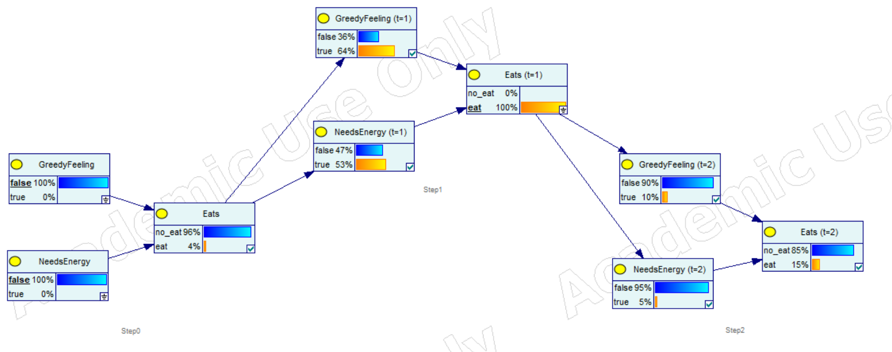

Figure 17: Dynamic Bayesian Network using GeNIe Modeler

In the purpose of easily understanding, we do not present in details the mathematics behind inference and parameter learning since they are quite the same than Bayesian Networks. At least, there are some adaptations to do in order to have EM algorithm and Forward-Backward inference propagation working [30]. We discuss in further section the implementation and interest of Dynamic BNs in online learning assessing.

4 SRL supports using BN and DBN

In this section, we show previous research which apply Bayesian Networks and Dynamic Bayesian Networks on concrete digital game environment. In this purpose, we will mainly focus on the Sabourin's studies [22, 38] since they are the nearer and best representing researches for our context. Moreover, the process is well explained and reliable.

4.1 Introduction of the research

In the first paper [22], researchers decided to run experiments which aimed at predicting the SRL class of someone. They stated that, since low SRL people are the ones who suffer the most from SRL features, they need to be detected early on and helped in their journey through a game, a platform or a course.

Nevertheless, they firstly had to run an experiment to show the difference between 3 categories : low SRL, medium SRL and high SRL students. So, they could examine the result and try to predict their category through series of collected data.

For this purpose, they used and managed a simulated game environment called Crystal Island. People had 55 minutes to solve a mystery without knowing anything else than the features proposed (taking notes ...). Thus, they were prompted to do a pre-test in order to collect 26 features which represent the candidates (emotion, goal set, personality ...). Then, at 4, 11 and 18 minutes, they received a small self-report about their feeling, their progress and whether or not they felt lost. Finally, at the end of the game, all the candidates went in a separate room to answer questions regarding the game (post-test).

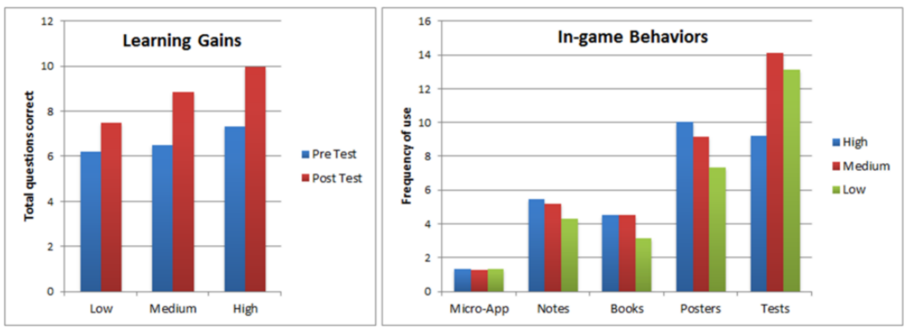

Figure 18: Learning gains and In-Game Behavior SRL groups from [22]

In the first place, they show that during the pre-test, candidates from low to high SRL had quite the same results (medium and high being just a little better than the low ones). But regarding the post-test, the results totally changed : low SRL progressed a little, medium ones did really well and high SRL were the best (Figure 18). Thus, they confirmed the fact that, beginning from the same point the inequalities through a environment that supports SRL were aggravated between the different classes. Moreover, they also compared the actions done by the students during the game and showed that some of the behaviors were part of the success of some of the students, **Fig. 2**.

In the second and last experiment, they try to predict the category of SRL of students during the pre-test, 4,11 and 18 minutes reports. They use several Machine Learning models such as Naïves Bayes, Neural Network, Logistic Regression, SVM, Decision Tree. As we can see, the results were quite balanced for the pre-test and first report. They reach at most 51.2% accuracy (which is better than 1/3). Without any surprise, the accuracy increases with the more data collected (second and third reports) and reaches at most 57.2% with the decision Tree. Regarding the experiments, it means that at 18 out of 55 minutes, we can detect with an accuracy of 57.2% a candidate's SRL class (Figure 11). This seems to be a better score but it also represents 1/3 of the total time to detect a SRL class (which can be a little bit late regarding real-life examples).

4.2 Using BN and DBN to improve results

Following their previous work, Sabourin et al. [38] reused the same experiments in order to try a new model : Dynamic Bayesian Networks (DBN). The intuition is totally justified since DBN are a subpart of BN using variables and conditional relations to represent a problem, but which follows Markov Theory. It means that, instead of having only one system, we have the same system over and over regarding a periodic event which in our case can be represented as pre-test, 4, 11 and 18 minutes self-reports.

Therefore, it totally fits the experiments since there are some dynamic data given by the game player's actions and choices and fixed ones which totally depend on the player. Moreover, the authors decided to create three variables which are an aggregation of all the variables :

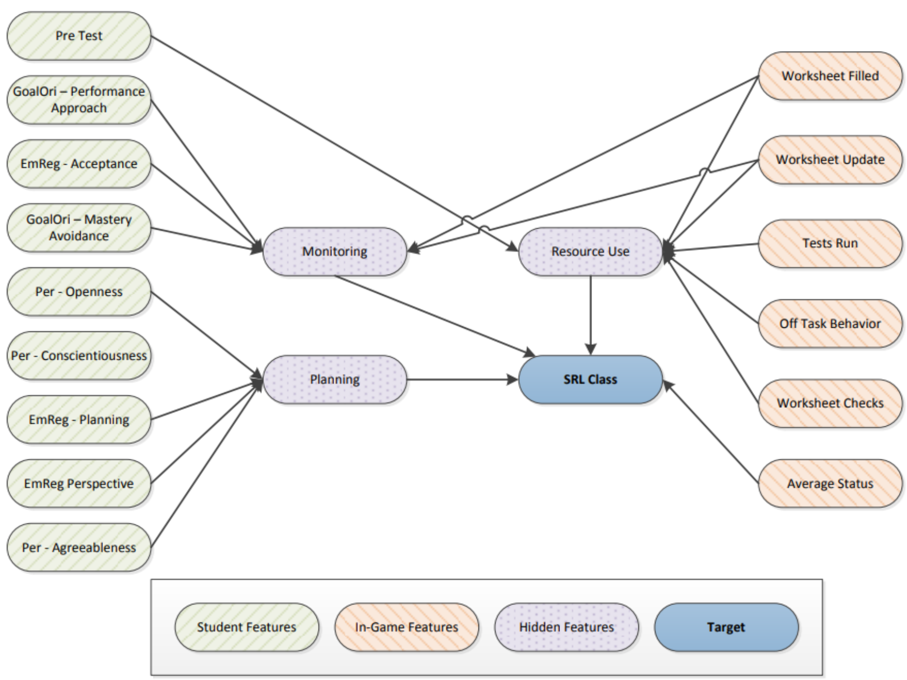

Figure 19: BN structure [38]

- **Resource Use** : In-Game behavior and actions
- **Planning** : How the students plan in new situations, handle cognitive emotions ...
- **Monitoring** : goal set, learning consciousness, use of worksheet ...

As we can see in (Figure 19), the authors chose to represent the aggregated variables as a dependency of in-game and students' features. Then, the SRL class is a variable dependent on the aggregated variables and the self-reports. Moreover, they selected only 15 of all the initial variables with a statistical test (to be significant). Finally, they decided to run the EM algorithm to approximate the Conditional Probability Tables. Notice that everything was produced with the help of the software GENIe, Thus, we obtain the following DBN :

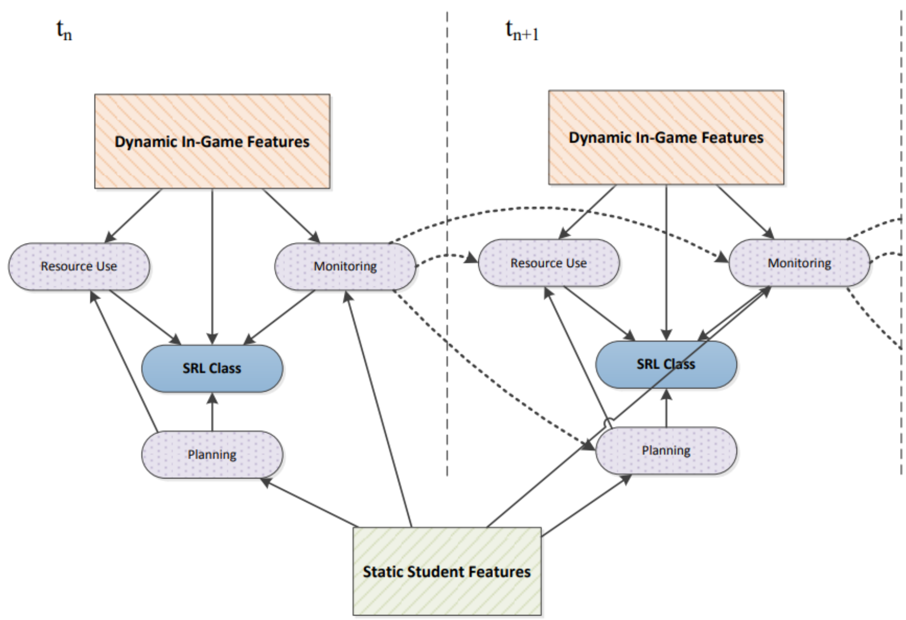

Figure 20: DBN structure [38]

(Figure 20) shows us the periodic structure of the DBN, that it is needed to be repeated 4 times in order to have every events of the experiment. We can see that, they chose to only select the Monitoring variable to represent the periodic dependency between events (Monitoring$_n$ $\perp$ Ressource Use$_{n+1}$, Monitoring$_n$ $\perp$ Planning$_{n+1}$, Monitoring$_n$ $\perp$ Monitoring$_{n+1}$).

Model	Predictive Accuracy Initial	Report$_1$	Report$_2$	Report$_3$
Top Prior Model	42.7	46.2	48.1	57.2
Bayesian Network	64.8	67.0	67.5	68.5
Dynamic Bayes Net	64.5	80.5	81.3	83.1

Figure 21: Predictive model accuracy [38]

Class	Bayesian Network				Dynamic Bayesian Network			
	Initial	Report$_1$	Report$_2$	Report$_3$	Initial	Report$_1$	Report$_2$	Report$_3$
Low	0.67	0.67	0.70	0.58	0.73	0.71	0.73	0.75
Medium	0.61	0.57	0.59	0.68	0.49	0.78	0.80	0.84
High	0.66	0.77	0.73	0.79	0.71	0.92	0.91	0.91

Figure 22: Predictive accuracy regarding SRL classes and prompts [38]

This architecture leads researchers to obtain promising results as we can see in (Figure 21). Compared to previous model results, the Bayesian network increases its accuracy of 20% in early stage and 10% at the last self report. This leads to, at least, more than 2/3 chance to predict the SRL class. But even better, the DBN obtain a score of 80.5% at the first self report regarding other results and the time spent in game. At the end, the model gains 3%.

Last but not least, In (Figure 22), we also observe that the DBN and BN struggle the most to predict low SRL class compared to medium and high classes. It ensures us to have a good classification for the ones who need less to be detected and a rather worse one for the other.

4.3 A synthesis of BN and DBN usage

As we may already have mentioned before, the results are quite promising since they offer a good accuracy early on in the process. Therefore, within 4 minutes, the DBN is able to isolate correctly the low class SRL with a 75% success. Classifying such students in these categories could help the worst ones to progress and maybe reach the medium or high classes in the next report, to correct the middle ones to reach the high class and finally, to try to raise even more the high class.

Nevertheless, we may discuss some aspect of the previous research :

- **Reproductibility** : In this paper, the major part of the data, the statistic methods and processes have been explained. However, we tried to obtain their data but we are still waiting for the answer. In addition, those types of data are hard to simulate since there is no information about their nature (range, distribution, type).
- **Conditional Probability Tables** : CPDs are really important if we want a model that fits the reality. In this paper, the EM algorithm was used to approximate them since they had no clue or reason to do it manually (with expert knowledge) [39]. This may lead to worse results and maybe some contradictions even if the EM algorithm is proven to be a good solution.
- **DBN dependencies** : Regarding the directed edges in the DBN, we may criticize the choices. Can we really say that the variables are dependent of Monitoring or that Monitoring is dependent of the variables ? They chose the second option and then this could be discussed. In another study [40], Gherasim et al. show a ”top-down” approach which considers the indicators ”state of the component” as a central variable on which other variables are dependent (”state of wind farm” and ”failing indicators”). This could be reproduced in this DBN by inverting some arrows between aggregated variables (Monitoring, Planning, Ressource Use) and candidates/in-game features.

5 France's IOI platform : quick-pi

In this section, we focus on the platform we choose to implement our modules and models.

Quick-pi is a web platform, built by France IOI, which is aimed at providing learning activities and challenges to high school french students. The main theme is connected objects and IoT. Learners enroll themselves in 3 learning paths : Discovering sensors and electronic equipment, Discovering memory and programming language specificity and finally advanced language structure and communication between devices. At least, Quick-pi receive a large traffic per year near 80.000 participants, and can be used by independent learners or classrooms. Thus, even if the targeted audience is still the same, learners do not have the same environmental structure and help seeking possibilities. However, on the platform, they will have to answer the same problems and exercises.

Each activity follows the same process : Before anything begins, the learner is prompted the programming language he wants to use between Scratch, Python and Blockly. Then, he enters the exercise panel where he can select one. Focusing on an exercise also call subject, the learner is facing an well-designed interface where he can program and solve the challenge. Regarding (Figure 23), the interface is segmented between several areas. Firstly, at the top of the web page, there is the basic information of the subject but also the activity as the number of cumulated points obtained when succeeding an exercise. Stars represents the difficulty also call version of the subject from two to four. Nextly, we have the subject's information and execution display on the left middle and upper side. This provides context and goal of the exercise, with in addition, help link for the learner. On the bottom left corner, there is the code execution control. It helps the students debugging, testing and be their own manager of the code's execution. they can control speed, step to step, go to end and validating their answer. Lastly, on the right side, there is the programming prompt where learners write code. Moreover, they have floating icons which enables them to seek help if they struggle.

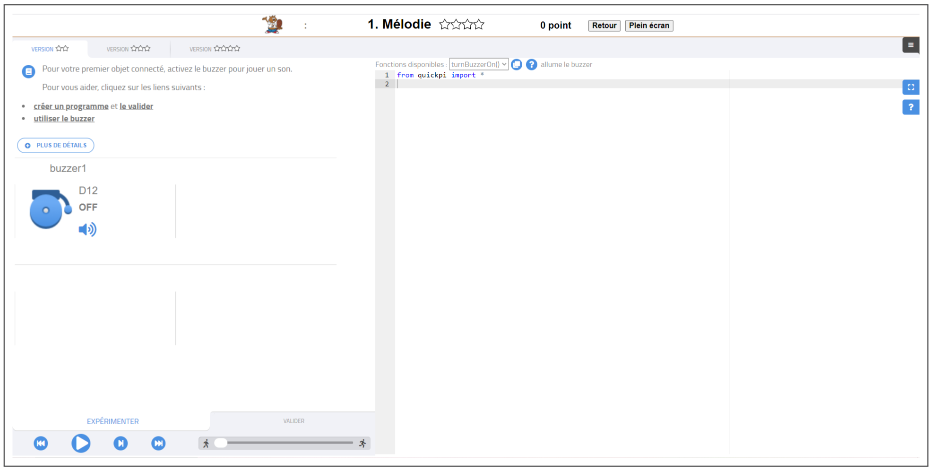

Figure 23: Quick-pi subjects interface

In the first time, we decided to only work with this platform. The learning process will not be followed during several activities, then we focused on a unique session to collect data, interpret them and propose solution to the learner.

6 Our contribution

In this section, we highlight our contribution to the research field and the learning process on quick-pi. In the first place, we show how we decided to collect data, then in a second point, we focus on our experiments and data exploration. Finally, we present the different strategies and models we use to predict SRL.

6.1 Data Collection

One of the most time-consuming aspect of this internship was to build a new module from scratch which will handle the collection of data on quick-pi. This module works on its own and is just called by the platform. It had to handle both, prompts drawing and interaction traces' collecting.

6.1.1 Timestamped Prompts

As one of the most important aspect of assessing SRL as we described in 2.3.4 and 4.2, we choose to use prompts as a manner to collect data on the learner thinking of one-self and self-regulated processes. We define three prompts which appear before, during and after the activity. But in order to have as accurate question as possible, we based ourselves on the SOL-Questionnaire. Since our audience is high school student, we greatly reduce the number of questions from the original questionnaire in order to take into account the time constraint of the activity but also the capacity of comprehension of learners. We only keep the most important aspect of this questionnaire, simplifying the most part while keeping the original SRL feature measured. Moreover, some of the questions were not accurate regarding the different process of learning in a MOOC and on a unique challenging session. We detailed the categorical and ordinal possible answers in the appendix 8.2.2.

Num	Question	Response	Category	SOL-Q questions
1	Have you already used quick-pi ?	Ordinal	Metacognitive Skills	1,2
2	Have you ever programmed ?	Ordinal	Metacognitive Skills	1,2
3	Where do you practice this activity ?	Categorical	Environmental Structuring and Help Seeking	22,23,24,25; 33,35,36
4	During this activity, do you think someone could help you often ?	Ordinal 5-Likert Scale	Help Seeking	32,34
5	What is the reason for you doing this activity ?	Categorical	Environmental Structuring	26
6	What is your goal ?	Categorical	Metacognitive Skills	3,4,5

Table 4: Initial Prompt

Firstly, we define the Initial Prompt (Table 4). It will appear to the user before the beginning of the activity in order to have several data regarding the context and the learner. You can refer to the Appendix 8.2.1 to see how it is displayed to the user.

Num	Question	Response	Category	SOL-Q questions
7	Are you motivated and interested in this activity ?	Ordinal 5-Likert Scale	Persistence	27,28,29,30, 31
8	How do you handle your time ?	Ordinal 5-Likert Scale	Time Management	19
9	Do you think you can reach your goal ?	Ordinal 5-Likert Scale	Metacognitive Skills	13

Table 5: Mid-term Prompt

Then, we define the Mid-term Prompt (Table 5). It will appear to the user at the middle of the activity in order to collect data regarding the feelings, the behaviors and self-consciousness of the learner.

Num	Question	Response	Category	SOL-Q questions
10	How have you handled your time ?	Ordinal 5-Likert Scale	Time Management	19
11	What do you think about your strategy in order to reach your goal ?	Ordinal 5-Likert Scale	Metacognitive Skills	9,18
12	Have you reach your goal ?	Ordinal 5-Likert Scale	Metacognitive Skills	9,14,18
13	Something else you want to tell us	Commentary	Out of SRL	-

Table 6: Final Prompt

Lastly, we define the Final Prompt (Table 6). It will appear to the user at the end of the activity in order to collect data regarding the result obtained, the thinking regarding goals and management of ones learning.

We are aware that considering SOL-Q, this prompt lacks some aspects or regroup many questions in one. We don't pretend to have the perfect prompts but we choose simplicity and understanding over accuracy on each concept. Moreover, we also are conscious of the fact that, Traces will help to collect data which will answer some of the questions of SOL-Q that prompts didn't.

6.1.2 Interaction Traces

In order to enhance our data through SRL perspective, we implement the collection of many interactions between participants and the platform. This enables to keep track of true actions unlike reported thinking of learners. In addition, it helps us simplifying the questionnaires / prompts asked to student in order to keep them concentrated in their task. The collection is stealth and done while the participant is taking actions. We define several interactions (Table 7):

Name	Description	Utility
Focus	If the user leave or get back to the web page	the user is doing something else, is looking for outside content
Navigation	If the user navigate on a platform's module (exercise, help ...)	keep tracking of exercise investment, organization of ones solving.
Modification	If the user change something in his solution, the size of code and potential errors	keep tracking of exercise solving evolution.
Mouse	The user movement and actions with the mouse input	keep tracking reading, playing behavior with the mouse.
Keyboard	The user actions with the keyboard input	keep tracking typing.
Step to step	If the user execute his code, with which speed and step to step or not	See if the participant try to understand, if he manages correctly his environment.
Validation	If the user validates or experiments his code, the score obtained and the potential error associated	what kind of error learners make, test strategy or not.

Table 7: Interaction Trace synthesis

As already mentioned before, those events doesn't mean anything alone. Their associated timestamp give better information to deduce behaviors, but the most interesting aspect is to be able to aggregate a set of continuing traces and give them accurate signification. Our aim is to be able to take into account aspect like strategy, environment usage and behavior. We detail with more accuracy our database model in the appendix 8.1.2.

6.2 Experiment

Unfortunately, due to Covid-19 and France IOI's deployment constraints, we encountered several problems before running correctly the validation of our prompts. In this section, we show our procedure from the deployment of our solution to the produced results.

6.2.1 Prompt Validation

Our first goal was to validate our prompts in order to be sure that they can be correctly answered by high school and younger students from middle school. Thus, we contacted several french high schools from the whole country. But we found ourselves blocked since we didn't receive any answers, this reduced the time that we could have given to the analysis and prediction part.

Luckily, we had the opportunity to test our prompts during 2 weeks with a remote professor and students. Since we haven't had the possibility to monitor this validation in front of participants, we should carefully consider the conclusion raised by this experiment. Firstly, the participant were all high school students. They were separated in half classes, running the activity for at least 1 hour in order to see and answer each prompts. Our aim was to collect their data and check the feedback from both the professor and students. Moreover, we had the opportunity to check, by an analysis of the data, the interest and the relevance of our questions.

However, we haven't had this chance because there were several problems during the data collection between our deployed module and the Quick-pi's platform. Thus, we only had left the feedback from the participants. Those were really useful, but we still remind that they should be considered retrospectively :

- Some of the questions' answers feel inaccurate. For example, we had to answer "I totally disagree" to the 7th question of our prompt. But even more, in french it is incorrect to formulate such answers. In this context, we should have chosen "Not at all". Thus, we corrected some of the answers to respect the french language.
- As for the answers, some of the questions were a bit confusing for the students. For example : "Is there someone to help you ?", 4th question, supposes that the students already know how often someone can help them while not knowing the activity yet. We changed it to "During this activity, do you think someone could help you often ?"

Else, the feedback were quite good regarding the content. Nevertheless, we still decided with the France IOI's approval to slightly change the presentation of our prompts for improving the overall process. This was aimed to help the deployment in production. For this purpose, we changed 3 parts :

- **Process** : Each of the questions of a prompt were presented in the same modal window. This leads the participant to scroll to answer all of them and not having any idea of the time it will take. Thus, we decided to put a single question on the modal window. The participant has to click on the validate button to continue with the next question. The question scrolls from the right to the center of the modal. In addition, we added a "step to step" bar which indicates the number of steps left to end the prompt (see the top bar of Figure 24).

- **Leaving possibilities** : One of the main constraints we imposed to our participant is that we force them to answer prompts unless they leave their browser. This is a problem since people who are forced to answer something may not give accurate results. Thus, we decided to give the opportunity to participant to leave at any time. They just had to click the red text at the bottom of the prompt saying "I don't want to answer anymore" (see the bottom red text of Figure 24).

- **Age** : Lastly we had to be aware that younger participants may also encounter those questions and struggle. Since they were targeted towards high school students, we added a question for the first prompt asking "Are you more than 14 years old ?". Participants were offered 3 answers :

  - **I am** : Then, the participant has to answer the prompts.
  - **I am not** : Then, the participant has no prompt to answer, he directly goes to the activity.
  - **I don't want to answer** : If the participant had no interest in answering us, he directly goes to the activity.

  We may notice that this question was not collected in our database, as we wanted to keep as much privacy from the students as possible.

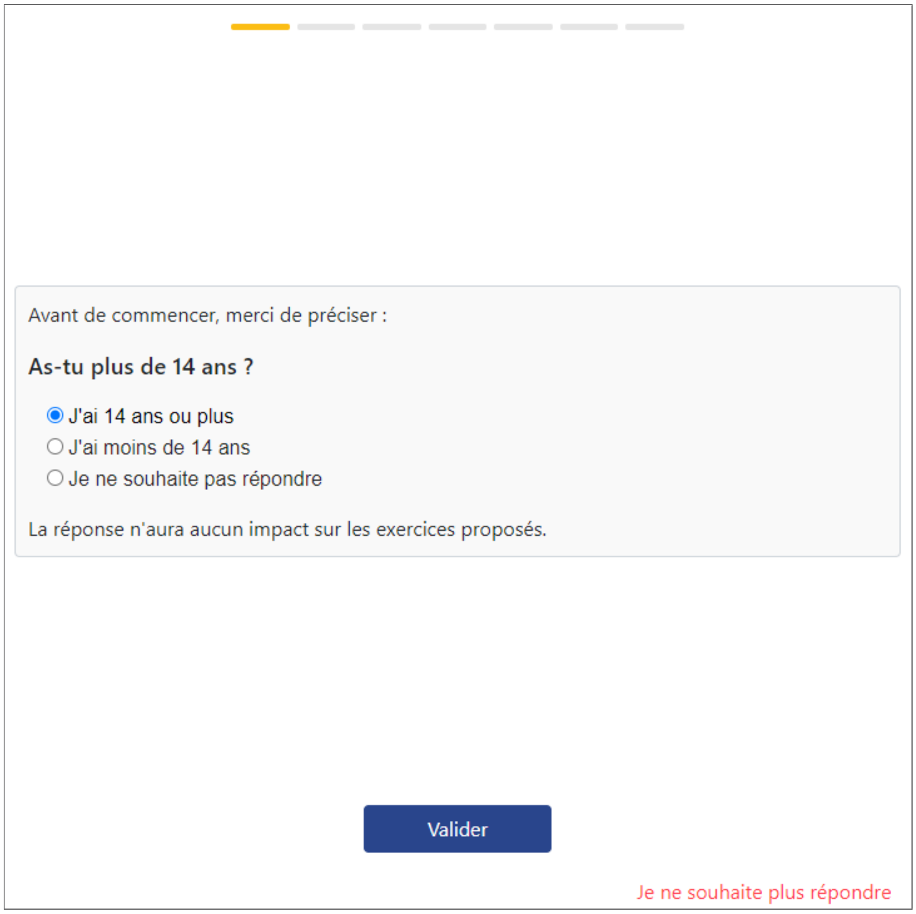

Figure 24: New prompts

Finally, we really lately deployed the prompts in production, as we handled the last bugs. Then, every remote participant had the opportunity to answer them. However, regarding web constraints and congestion, we also decided to deploy it, only for 10% of the participants. After 2 weeks of data collecting, we could pursue with the data exploration.

6.2.2 Data exploration

In order to understand our data, to propose accurate solution and indicators for the Bayesian Network, we had to conduct several Data Analysis and Visualizations. Since this part was conducted two weeks before the end of this internship, there might be some adjustments and findings that we didn't have the time to do. Firstly, we explain how we selected the participants to create our dataset. Nextly, we show how we aggregated some of the collected data with the intention of observing the exercise's difficulty. Then, we suggest interesting visualization and findings. Lastly, we discuss those analysis.

6.2.2.1 Participant's selection

One of the main goals with this database is to sort participants in a way that we can correctly compare one to another. Firstly, in order to understand our process, we have to give back the context. As the module is in production, Quick-Pi's platform receives a lot of participations each day. For example, three weeks after the module was deployed, we obtained a number of 5044 connections with the SQL request :

```sql
SELECT COUNT(id) FROM connexion WHERE id > 191
```

Where id = 191 corresponds to the last id which was a test for the deployment. Moreover, some of the connections were from the same participant, even if they just represent a small proportion of the participants (less than 5%).

Due to this important number of connections, we had to find an accurate way to get trustworthy participation. Thus, we propose the following process :

- **11th Activity** : The participation has to be related to the 11th activity. This activity represented more than 80% of the connections. Moreover, 11th activity has 10 subjects of different versions. It enabled us to compare our participants on the base of the same resources to learn with.

- **At least one hour** : Our aim is to compare people with and without prompts on the same base. In this objective, we chose to cut every connection from its beginning to its beginning plus one hour. Then, we eliminated a lot of connections which only lasted for few minutes.

- **At least one positive validation** : During one connection, the participant should have achieved at least one validation of his code, which was verified and classified as correct by the platform. This single condition helped us to eliminate participants who connected themselves but didn't try anything or may have forgotten to close the browser. In addition, we ensured that it exists at least one validation from the participant, meaning that he has explored a little more the platform than just doing experimentations.

With all conditions respected, we obtained a total of 93 connections, which were all from different participants after verification. We are aware of the fact that it only represents a small subset of individual, if we had more weeks to collect data we may have doubled the amount. Nevertheless, Bayesian Networks are known to be used with expert knowledge when numerous data are missing.

Yet, we faced another unscheduled problem. Regarding all of our 5044 connections, none of them contained the 3 prompts. None of them had the final prompt, few had the middle one and some had the initial prompt. Unfortunately, since the time was too short to change something, we decided not to use those the prompts' data. There may be four options to explore in a future study :

- Deploying only for 10% of the connections is too low to collect prompt's data.
- Giving the choice to the participant to quit at anytime the prompts may lead them to not do it.
- The prompt is seen as a waste of time or is not attractive enough to participants.
- All the prompts were shown for less than one hour's connections.

6.2.2.2 Subject Oriented Visualization

In this section, we present relevant information shown by visualization. The data are aggregated with the subjects they are related to, this enables us to understand more about our platform and activity. In each of the plots, subjects were ranked in the same order in which they were ranked for the student such that : Subject 20 match with the first subject of the 11th activity.

In the first place, if we consider the number of times a subject was completed (positively validated) by participants (Figure 25), we clearly see that the higher the subject is in the rank, the less it will be validated by participants. It confirms the fact that, France IOI tried to rank them by their difficulties (independent from version). But we may confirm it with the time spent by subjects (Figure 26), else it could be a bias since participants may not have much time to spent on the last exercises. At least, this plot shows us that people invest nearly the same amount of time in each of the subjects (not versions). Thus, it means that some of the subjects are really harder than others. In addition, we also observe that subject 21 version 4, which is the second in the order was really hard for student. It was the least validated subject/version and the most time consuming.

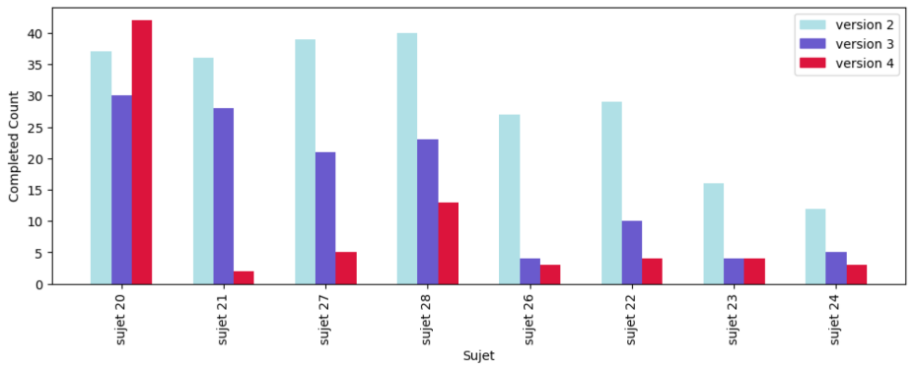

Figure 25: Number of times subjects were completed per version

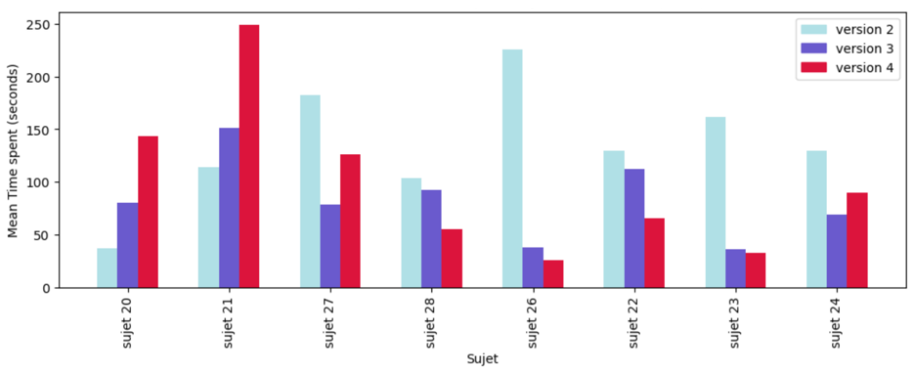

Figure 26: Mean time spent on subjects per version

Furthermore, if we now compare the mean number of experimentations and validations on subjects per version (Figure 27,28), we can see that especially on the first subject, participants ran a lot more experiments than on the last subjects. This probably means that at the beginning, they were not comfortable with the quick-pi environment and the type of subject proposed, they experimented more in order to correctly understand what we ask them. It could also mean that the participants judged that experimenting was a waste of time, the more they are comfortable with the platform. This may be confirmed by the number of validations. Indeed, the number of validations decrease but way slower than the number of experimentations per rank of subjects. It may also explain why students are less completing subjects ranked at the end, if they badly estimated the difficulty of the highest ranked subjects and didn't do experimentations anymore, they probably reduced their success rate.

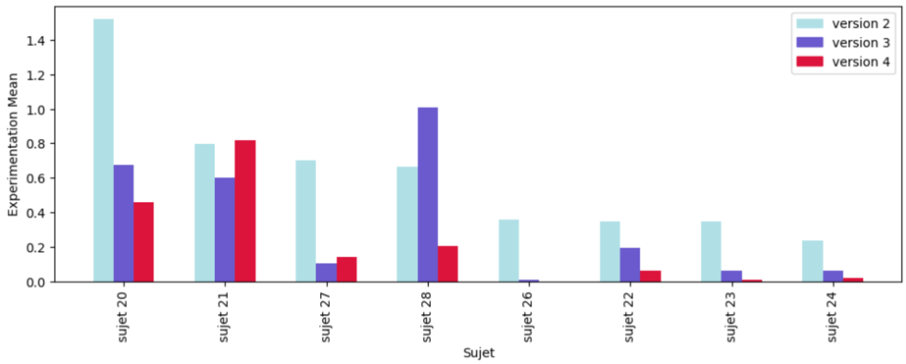

Figure 27: Mean number of experimentations on subjects per version

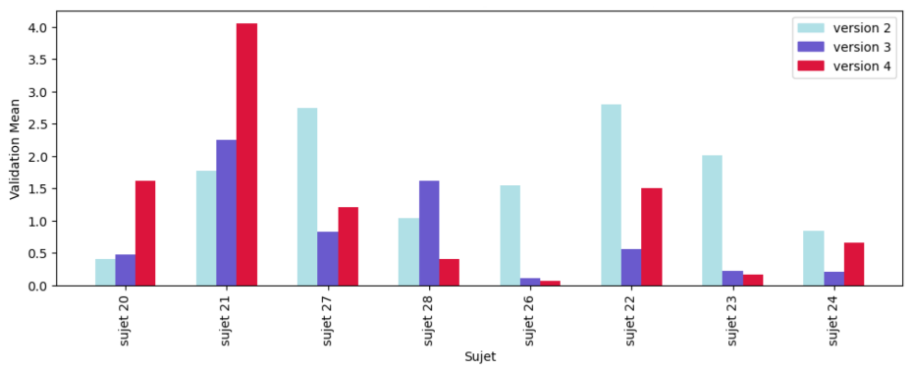

Figure 28: Mean number of validation on subjects per version

Those findings are well confirmed by the time spent on the help module (Figure 29). As we said, participants who just discovered the platform consulted the help module a lot more regarding subject 20. However, it seems that they estimated it not necessary anymore for the most part of other subjects. Mostly in this case, we see that help module is not really consulted by participants. Regarding the cumulated score distribution (Figure 30,31), they may have taken the wrong choice. It confirms what was found in previous studies such as those of Young [12]. In fact, the distribution of scores seems to follow a Beta Distribution, concentrating the most part of the participants under the score of 100 and the minority upper 100.

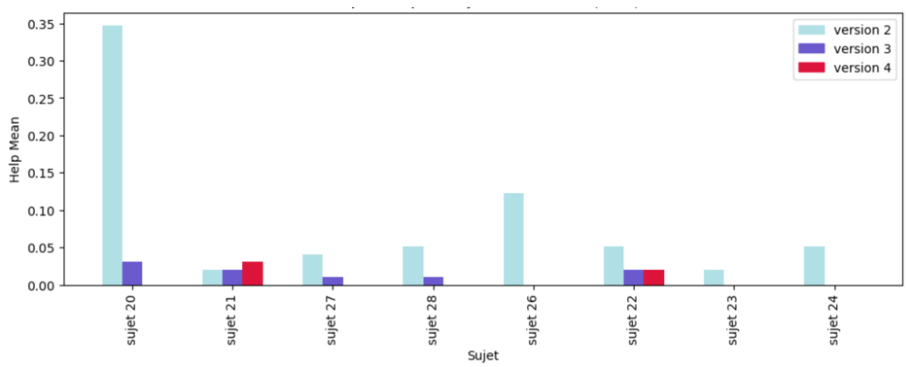

Figure 29: Mean time spent on help of the subjects per version

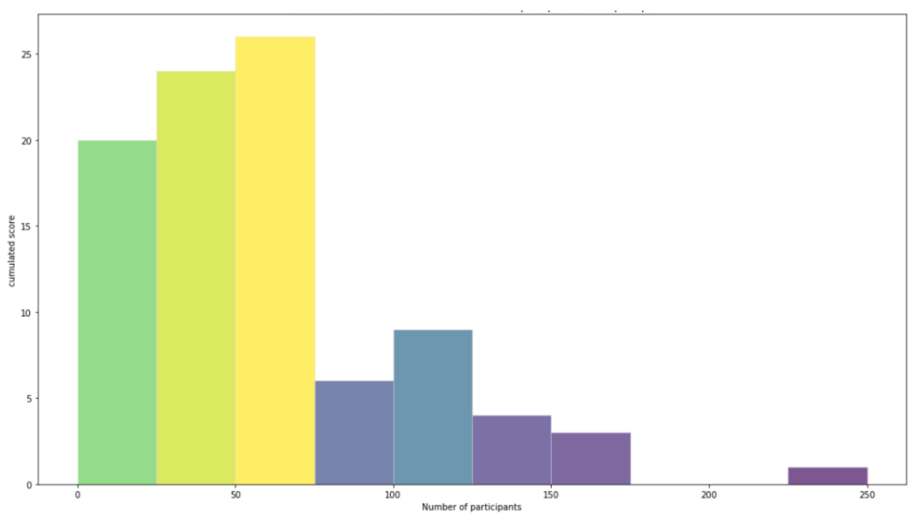

Figure 30: Cumulated Score distribution at the middle of the activity

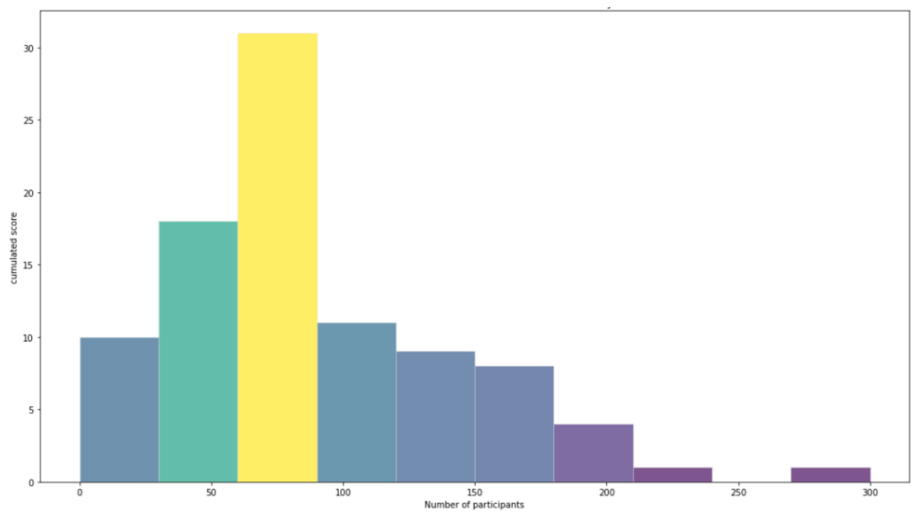

Figure 31: Cumulated Score distribution at the end of the activity

6.2.2.3 Discussion

Regarding previous statements, we may discuss the findings and propose improvements for future researches. To begin with, we want to show that the participants' selection should be improved. Indeed, filtering participants on such previous criteria helps to have an idea of the "real" participants, those who correctly run the activity without being absent and keeping the browser opened. We want to focus even more on those who are included in the current filter, some of them may participate during a time frame lower than 1 hour but still keep their browser open while not doing anything until the end. In addition, further verification should be done on their traces to be sure that they are reliable participants.

We propose further visualization in order to better understand the data and the interaction between traces. For example, it could be interesting to look for a participant oriented visualization where we can follow his path through the whole activity and show specific interactions happening at a certain timestamp. This will probably give important information and help creating new variables or indicators which rather fit the reality and the context of the Quick-Pi's platform.

Finally, we emphasise the fact that our dataset may be too small to give such interpretations, further work may have access to more data and thus, improving the confidence in our findings.

6.2.3 Bayesian Models

Since we now have a deeper knowledge of our data, we can propose our prediction models based on BN and DBN. In this section, we show how and why we selected indicators as variables for our models, then we explain the hypothesis we have done with the structure and expert knowledge. Finally we present the results and discuss them.

6.2.3.1 Variables

In the first place, our aim is to predict the SRL Class of a participant. For this purpose, we need to define what makes a Low, Medium and High SRL's skilled participant. Regarding Sabourin's [38] dataset and ours, there are some differences. Firstly, the authors produced a questionnaire that students had to answer before the activity. Then, they associated a label corresponding to the SRL Class to them. In our case, we proceeded in a slightly different way. Due to the fact that we don't know anything before the activity of the participants, our only way of classifying them is by creating a relevant indicator from the traces. Thus, we chose the accumulated score regarding validated subjects. It helped us creating an easy labeled variable and showed the capacity to succeed in a environment which supports SRL such as Quick-pi. Moreover, we have to detail the way that the score is computed :

- $v_{i,j}$: Version $j \in [2, 3, 4]$ of Subject i
- $score = \sum_i max(v_{i,j}) * 10$

In a second point, we defined the observed variables which has enriched our models :

- **Validated Time Rate (VTR)** : One important indicator is to know whether or not a participant spent much of his time doing something he has/will validate during the activity. This variable helped us to show both Time Management and the capacity to monitor one's own learning process through success.
  Computation :
  - Define the subset of subject which have been validated : I
  - x_i : Time spent on the subject $i \in I$
  - h_i : Time spent on the help module of the subject $i \in I$
  - T : Total time spent since the beginning of the activity
  - $VTR = \frac{\sum x_i + h_i}{T}$
- **Highest Version Mean Validated (HVMV)** : Since score highly rely on versions validated, it is a good indicator to keep track of the mean of difficulty the user was able to succeed. It gives us the performance of a participant but also the strategy he planned, for example : validating several low versions rather than just a few high versions.
  Computation :

- Define the subset of subject which have been validated : I
- Define the subset of pair (subject, version) which have been validated : J
- $v_{i,j}$: Version of a validated (subject,version) $(i, j) \in J$
- $HMVV = \frac{\sum_{i \in I} max(v_{i,j})}{|I|}$

- **Time Consulting Help (TCH)** : Participant are offered a help page were they can have code's documentation, easy resources which helps to understand the current subject that they are doing. Thus, it both represents two aspect of SRL : the correct usage of the resources at disposal and the planning ability to stop one's exercise resolution temporarily to improve comprehension of the subject and then validating it quicker.
  Computation :
  - Define the subset of subject : I
  - h_i : Time spent on the help module of the subject $i \in I$
  - $TCH = \sum_{i \in I} h_i$

- **Mean Test Per subject (MTPS)** : The participant can interact in two ways to test his code : by experimenting with the step to step interface or validating with the approval of the platform. Thus, in this indicator we merge both since participant use both to test their solution. Thus, we obtain a number of tries per subject which indicates if the user has a strategy of hyper-testing or thinking between each test.
  Computation :
  - Define the subset of subject : I
  - v_i : number of validation of the subject $i \in I$
  - e_i : number of experimentation of the subject $i \in I$
  - $MTPS = \frac{\sum_{i \in I} e_i + v_i}{|I|}$

- **Mean Size Modification Per Test (MSMPT)** : Quick-pi's platform collects log events when the user modifies his code. The associated code produces a length which we store. Knowing the difference of size between two tests can show if the user uses a new approach or just brings some adjustments to his solution.
  Computation :
  - Define the subset of test (validation and experimentation) : I
  - m_i : the last modification size of the test $i \in I$
  - $m_{i'}$: the last modification size of the test $i' \in I$ coming after test $i \in I$
  - $MSMPT = \frac{m_{I[1]} + \sum_{i \in I} |m_{i'} - m_i|}{|I|}$

- **Mean Modification Per Subject Tested (MMPST)** : This indicator provides a mean value of modification per subject. It indicates if the student had a lot of trouble finding the solution or if he preferred to do a small number of modifications.
  Computation :
  - Define the subset of subject tested : I
  - m_i : the number of modification of the subject $i \in I$
  - $MMPST = \frac{\sum_{i \in I} m_i}{|I|}$
- **Mean Time Active (MTA)** : In addition, we want to observe if the participant was quite active on the platform or rather distracted, thinking outside of the computer. For this purpose, we followed the mean time between each traces ordered in time.
  Computation :
  - Define the subset of event collected ordered in the time : I
  - t_i : the timestamp of the event $i \in I$
  - $t_{i'}$: the timestamp of the event $i' \in I$ which follows the event $i \in I$
  - $MMPST = \frac{\sum_{i \in I} t_{i'} - ti}{|I|}$
- **Experimentation Quality (EQ)** : Experimentations provide useful information on how the students monitors himself throughout the learning process. Moreover, there are different levels of experimentation : some may be done quickly, with few changes, without any help consultation. These are classified as bad experimentation since they came from adjustments. Additionally, experimentations can be more valuable to the participant when he has consulted the help module before.
  Computation :
  - Define the subset of experimentation : I
  - s_i : the subject of the experimentation $i \in I$
  - h_{s_i} : if the user has consulted the help module of subject $s_i, i \in I$
  - m_i : the number of modification before the experimentation $i \in I$
  - $mlast_i$: if the last modification before the experimentation $i \in I$ has an error
  - $EQ = \frac{\sum_{i \in I} 0.25 * h_{s_i} + 0.25 * (min(10, max(m_i, 10)))/10 + 0.5 * mlast_i}{|I|}$
- **Validation Quality (VQ)** : Similarly to Experimentation, Validation should only be used when the participant thought his experimentations were correct. However, some use it as experimentations and thus do not use step to step resources. It is then important to know the quality of validation to evaluate the monitoring capacities of a participant.
  Computation :

- Define the subset of validation : I
- s_i : the subject of the validation $i \in I$
- t_{s_i} : if the user spent at least 1 minute on the subject $s_i, i \in I$
- tre_{s_i} : if the user has spent at least 1 minute between the last validation on the subject $s_i, i \in I$
- $verror_i$: if the last validation $i \in I$ has an error
- e_i : if the user has done experimentation before the validation $i \in I$
- $VQ = \frac{\sum_{i \in I} 0.10 * t_{s_i} + 0.15 * tre_{s_i} + 0.25 * e_i + 0.5 * verror_i}{|I|}$

6.2.3.2 Structures

Since our variables are defined, we propose a structure which will be inspired from the paper of Sabourin [38]. In addition, we also implemented hypothesis through expert knowledge in conditional probabilities.

Firstly, we produced a BN (Figure 32), with the observed variables in green. Each of those variable has to be categorized and each of the intervals for those categories was found using statistics and distributions. We also decided to create three values for each of the unobserved variables : Planning, Monitoring and Resource Use. Since we do not control how those categories will be interpreted by the learning algorithm, we used expert knowledge. Finally, after observing that Low and Middle SRL class were not correctly distinguishable, we decided to merge them in a single class. The scores of the Middle SRL class were too low to really match to such participant. Then, we obtained only two classes to predict : Low and High.

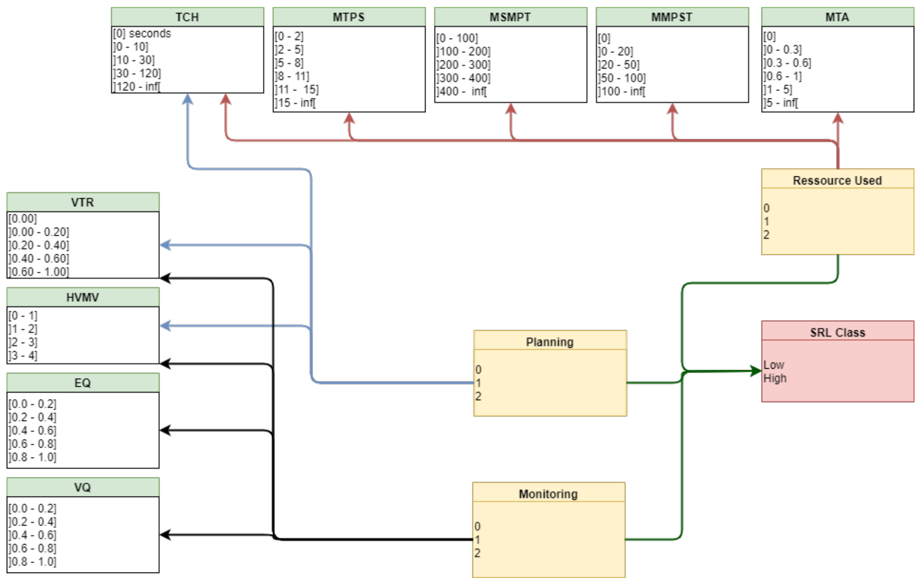

Figure 32: BN structure and state

In addition, in order to complete the small amount of data we have, we specified expert knowledge on certain conditional probabilities. The produced hypothesis were quite simple :

- For Experimentation Quality and Validation Quality, the same table was used (Figure 33), we decided to put more emphasis on high quality when the highest value of Monitoring was observed and lowest quality when the lowest value of Monitoring was observed. It means that we supposed low SRL participants will have low quality of validation and/or experimentation.

- We also put some knowledge in Validated Time Rate and Highest Version Mean Validated. As always, the higher Planning, Monitoring or Resource Use class were, the higher the variables values were. When there are two parents for an observed variable, the same weight was given to each parent. Thus, we expected high SRL participant to have a better mean over validated versions and time spent on validated subjects.

- For Mean Modification Per Subject Tested, we slightly changed the higher Resource Use to the middle values. It means that we expect high SRL participant to do medium modification and low SRL participant to both not modify (may abandon) or modify too much.

- Finally, we also put knowledge in the SRL class. The higher Monitoring, Resource Use and Planning were, the higher the class was. Each of the parent has the same weight, so the CPDs evolve linearly.

Monitoring	Classe1	Classe2	Classe3
Classe1	0.33333333	0.11111111	0.11111111
Classe2	0.22222222	0.22222222	0.11111111
Classe3	0.22222222	0.33333333	0.22222222
Classe4	0.11111111	0.22222222	0.33333333
Classe5	0.11111111	0.11111111	0.22222222

Figure 33: CPDs of Experimentation Validation

If we now consider the Dynamic Bayesian Network (Figure 34), we copied our initial BN with the same expert knowledge between variables and added dynamic links from the Monitoring (t=0) to the Planning(t=1), Monitoring(t=1) and Resource Use(t=1) variables.

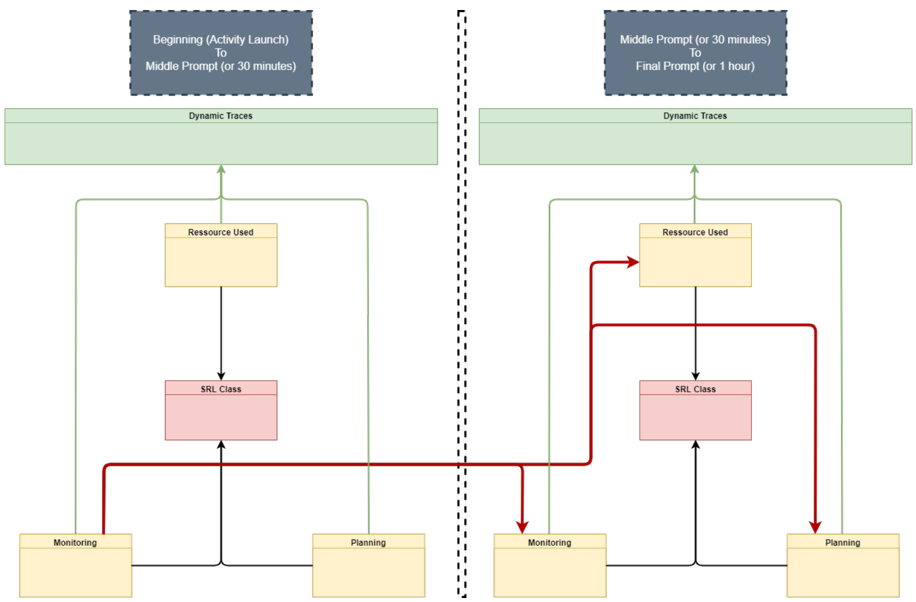

Figure 34: DBN structure

6.2.3.3 Results

In order to implement, predict and validate the results of our networks, we decided to use GeNIe which is a graphic tool developed by Bayes Fusion for probabilistic models' manipulation.

Our problematic is such that : we seek to filter the final SRL class (t=1) at each timestamp. In Dynamic Bayesian networks, filtering is the action of evaluating a specific variable which has a timestamp t, by observing at every timestamp $t' : t' \leq t$, all observed variables which have a timestamp $t'' : 0 \leq t'' \leq t'$. In this perspective, we chose not to affect values to the first SRL class (t=0), so this variable will also be unobserved. Concerning the SRL class (t=1), we defined two intervals : 0-99 for the class Low and 100-400 for the class High as our labels. These were computed from statistics and distributions. At the end, we obtained 62 low SRL and 31 high SRL participants.

Thus, we have to filtered twice, one time with the observed variables (t=0) and another time with all observed variables from (t=0) to (t=1). We used the "Validate" function which comes within the GeNIe software. This method proposes several options, but we chose specific ones :

- K-fold cross validation. It enables, with a small dataset, to train k times the model and validate k times with different samples. In our validation, we chose k=10. K-cross validation is one of the most robust method for validation with accuracy.

- We chose to sample the CPDs during the learning process by keeping the original, meaning that we consider our expert knowledge as a correct sample for the beginning of the learning. Our confidence factor was 1, the default value for GeNIe.

- We chose the SRL Class (t=1) as our filtered node. So that, the algorithm of validation will consider the argmax of this variable as the predicted label. Thus, it will compare it to the actual label of our dataset.

Finally, we obtained the following results (Table 8). As we can see, the indicator chosen was the accuracy. If we consider firstly the Bayesian network, we can see the filtering was more accurate on the SRL class (t=1) when the network had only the observed variables from the first timestamp (t=0). However, when the networks receive all data aggregated from (t=0) and (t=1), the BN was not able to improve its results. Since Bayesian network doesn't represent a sequence, it seems plausible that the score can decrease between each timestamp even with more information.

Nevertheless, while DBN struggled a little bit more at (t=0) than the BN, it outperformed by 15% accuracy at (t=1). It shows that the network has captured some essence of the model dynamics. Finally, we obtained a mean accuracy of 0.72 with the DBN and 0.69 with the BN. Rather than just a mean, the DBN improves himself while collecting more data, which is a good opportunity in such activity.

Model	Accuracy with O.V. $t \in [0]$*	Accuracy with O.V. $t \in [0,1]$*	Mean Accuracy
Bayesian Network	0.720430 (67/93)	0.655914 (61/93)	0.688172
Dynamic Bayesian Network	0.645161 (60/93)	0.795699 (74/93)	0.720430

Table 8: BN and DBN accuracy

* O.V. : Observed Variables.
* t : timestamp.

Looking at confusion matrix also gives important information such that, for the BN and DBN the first timestamp (t=0) makes it harder to predict the high SRL class (Table 9,11). For example we have a $21/31 = 0.67...\%$ and $10/31 = 0.32...\%$ respectively of accuracy for the High class while having $46/62 = 0.75...\%$ and $48/62 = 0.77...\%$ for the Low class. This also could be a bias due to the fact that the distribution of the classes in the dataset is 2/3 low, 1/3 high. But if we look at the timestamp (t=1) (Table 10,12), we see that there is no bias and that the problem may come from the lack of differentiation in data during 30 minutes. We obtained a $26/31 = 0.84...\%$ accuracy for the DBN high SRL class, which is the highest improvement over time.

	Predicted Low	Predicted High
Actual Low	**46**	16
Actual High	10	**21**

Table 9: BN Confusion Matrix with O.V. t=0

	Predicted Low	Predicted High
Actual Low	**43**	19
Actual High	13	**18**

Table 10: BN Confusion Matrix with O.V. t=1

	Predicted Low	Predicted High
Actual Low	**50**	12
Actual High	21	**10**

Table 11: DBN Confusion Matrix with O.V. t=0

	Predicted Low	Predicted High
Actual Low	**48**	14
Actual High	5	**26**

Table 12: DBN Confusion Matrix with O.V. t=1

Last but not least, those results were found in a few days of work. Having more time to invest and maybe better exploration, we could have created better indicators and structures to fit reality. However, results are promising and show that Dynamic Bayesian Networks may lead to better results than other models.

6.2.3.4 Discussion

Following our findings, we discuss both variables, structure and the dataset. In the first time, due to a small amount of time, our dataset was still small and we didn't have the opportunity to collect more diverse profiles of participants. Such that, we only obtained one participant going over 300/400 as his cumulated score, while the majority of participants were stuck between 50 to 150. This may show that our intervals selected to create our labels may be partially wrong with a larger dataset, as the other intervals for the categorization of the variables may be. Moreover, we also switched from 3 classes to 2. In fact, there are probably 3 classes in reality but the lack of data and good indicators may not differentiate them.

We have also not explored the data generation through a known dataset or a learned Dynamic Bayesian network. This could be a further step to drive better results and collect more data.

In addition, variables can be quite discussed for some of them, especially if we focus on the variables linked with Resource Use. The conditional probabilities were not so different from one class to an other, leading to difficult differentiation by the model. We may improve those variables by adding some, deleting others or modifying existing ones. Furthermore, each variable had some values which were determined by visualization and statistics. We may find more reliable way of determining them.

One point not to be missed is also the process of creating our labels. We can discuss the fact that, using a score as a mean to compute a SRL class may be partially wrong since we hope to find SRL features and not the performance in an SRL environment. We may associate the score with other weighted features that may indicate better SRL High or Low behaviors.

Moreover, we chose to consider the unobserved variables as the parent of both SRL class and observed variables. This also could be discussed since the dependencies between variables may change the overall relation and results. Looking at the dependency between each timestamp in the DBN, we decided to inspired

ourselves with the Sabourin's article [38] which propose an order 1 dependency between Monitoring (t=x) and unobserved variables (t=x+1). We can try to create more complex dependencies between each variables in order to improve the results.
Finally, the expert knowledge put into some of the conditional probabilities seems to work correctly but should be also reworked deeper. The linear and symmetrical evolution of probabilities, the same weight used for parents may slightly change the reality. But we should keep in mind that without this knowledge, our networks were under-performing.

7 Conclusion

Whether in the literature or in this report, Dynamic Bayesian Networks have proven their usefulness in supporting the self-regulation learning in online environments. We showed that they were able to correctly classify more than 3/4 of the participants regarding their SRL capacities on the Quick-Pi's platform. With further improvements, we could even reach better results.

This also supports the fact that, using such predictions to help the participants early on in the process may be the future step to look for. By isolating the indicators and the specific interactions between the participants and the platform, future researches may find interesting leverages to interact directly with the participant during their learning process. Then, it creates new opportunities to help the ones having trouble and understanding SRL features of a platform.

Last but not least, even if the results are promising, future researchers should not forgot the importance of the emotional impact and self-reporting of one's learning in such activities. Learning Analytics and traces studies may obfuscate those aspects by not giving any specific information about it. Prompts may be a good solution to follow one's investment and emotional behavior. Nevertheless, we also faced problems raised by the fact that prompts may be unattractive to under the age of majority participants.

8 Appendix

In this section, we will discuss of the architecture we built in details.

8.1 The architecture

We were offered two main possibilities : the first one was to create a module which will be integrated into the main targeted platform of France IOI. The advantage is that everything works on the same website and it doesn't require new web servers. However, we rather chose the second option which is to create a separate module from front-end to back end and database. It will only be called by the platform when needed. Even if it represents more hardware components or containers, this process helps us to generalize for every France IOI's platform and then easily maintain and propagate the module.

8.1.1 Architecture

In order to collect and transmit data to our back-end and database, we developed a front-end module using the framework React.js (Javascript based). This module will also use the JSChannel framework or HTML IFRAMEs, which helps to import a web page into another one and use all the inner Javascript functions. Then, it enables us to create a separate front-end with his own function, which handle JSON formatting of the collected data and then push them into a back-end API. As stated before, we choose to have a single array to transmit specific object in JSON, enabling us to send data with handling congestion and timers avoiding us to lose some important data due to unwanted disconnection or a bad manipulation of the users.

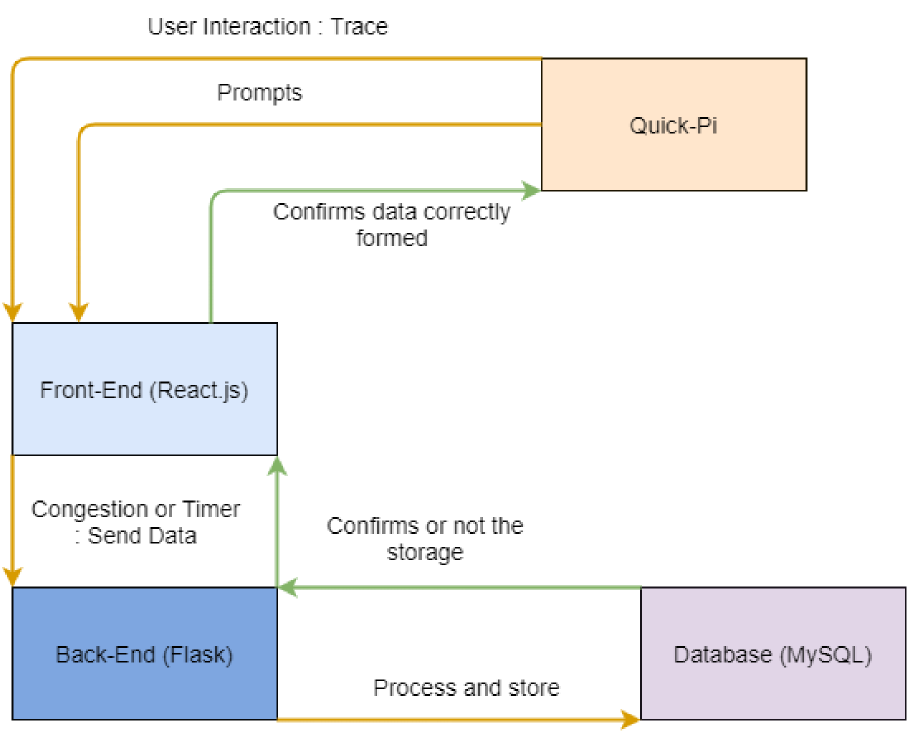

Figure 35: Interactions between modules

Moreover, the module also contains the SRL prompt : Initial, In-Real Time and Final. They just need to be called through a function or will be shown at various regular intervals (In-Real Time). Then, every prompt is handled in our side and helps us to easily modify the code without focusing on the France IOI's platform. Finally, all the design needed to be minimal as France IOI's design chart wants to adapt on the most web navigators possible (even really older version) with the less complicated design possible. Thus, we used the Bootstrap's framework with its easy responsive and simple designed component.

In the second place, we developed a back-end API in Python 3 using the Flask framework. We choose this language because it is one of the most known and complete for AI generally speaking. Considering Flask which is a really great tool to simplify REST API due to its swaggers, we mainly choose it since it is one of the most accepted web framework for python. This server handles and receives JSON data and process them (check, refactoring, add information), they are formatted respecting a JSON Schema validator, enabling security and reducing errors. Then, it sends every piece of information to the MySQL database. It uses the REST technology to handle asynchronous call from various front-end member called on several computers. In the first time, this server is only dedicated to brute storage of information coming from the France's IOI platform, but after, we also decided to deploy our models and response to our model's results.

8.1.2 MySQL database

We decided to use MySQL conceptor to show the relation between our tables. Moreover, Participant are identified by a unique URI which doesn't give any personal information.

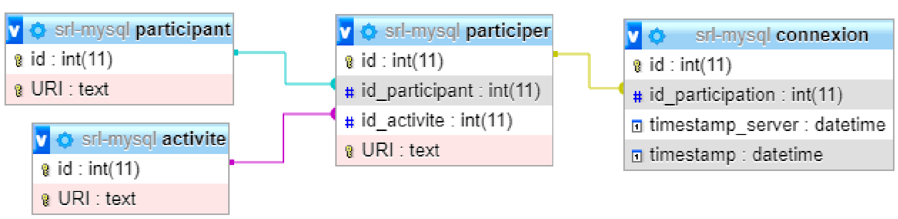

Figure 36: Basic Relations

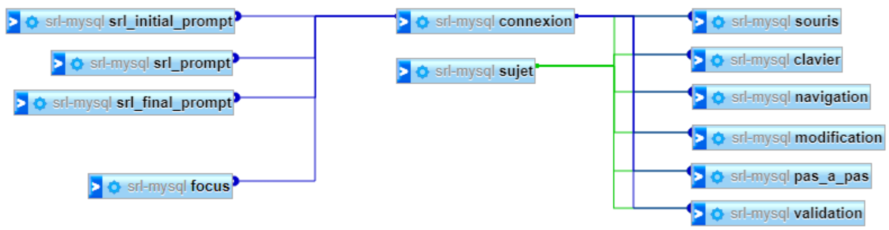

Figure 37: Traces and Prompts Relations

One participant should involve in an activity thanks to the participate table. Then, he can have disconnection or several-days course for one activity, the connection table handle those behaviors (Figure 36). Thus, every prompt and the focus table is linked to a connection. Moreover, the other traces tables are also linked to a subject (Figure 37). We can finally easily get the whole process of logs only by knowing a participation.

8.2 Prompts

In this section, we show and describe our prompts with more details.

8.2.1 Interface

The interface was realized with Bootstrap's framework and CSS/SASS stylesheets. It is purified but style warm-full for a high school audience. We have three types of data such that :

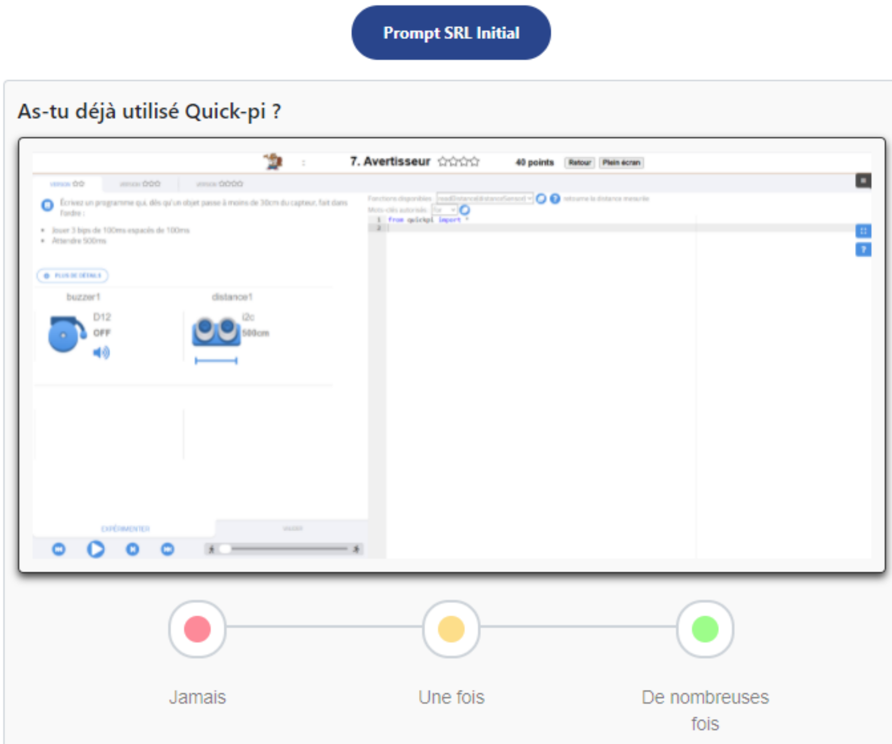

Figure 38: Ordinal Non-Feelings Question : Num 1

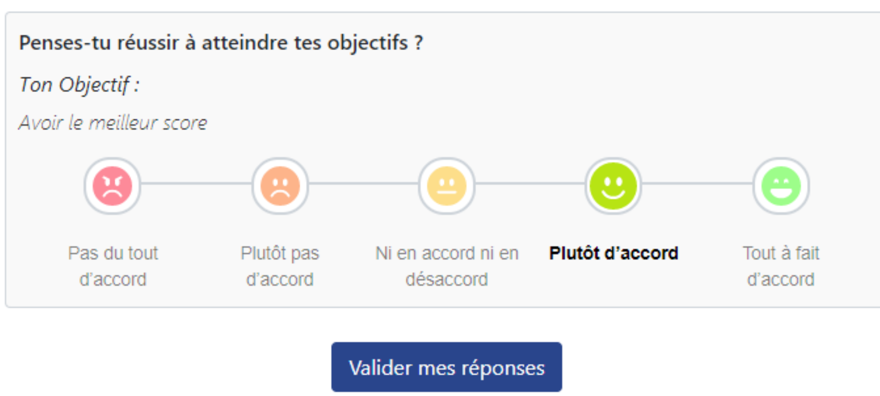

Figure 39: Ordinal 5-Likert Question : Num 9

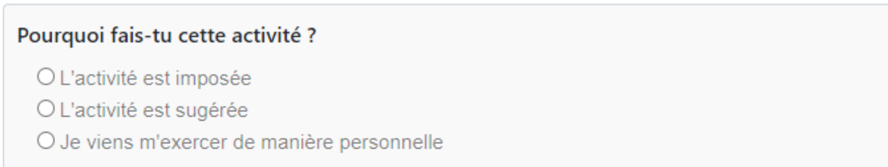
Pourquoi fais-tu cette activité ?
- L'activité est imposée
- L'activité est sugérée
- Je viens m'exercer de manière personnelle

Figure 40: Categorical Question : Num 5

8.2.2 Answers Description

We describe here in a more accurate way our prompts' answers. We also added conditional questions.

- **1** : Have you already used quick-pi ?
  - Never
  - One time
  - Several Times
- **2** : Have you ever programmed ?
  - Never
  - One time
  - Several Times
- **3** : Where do you practice this activity ?
  - At home
  - At school
- **4** : During this activity, do you think someone could help you often ?
  - I'm in total autonomy
  - Very rarely
  - Sometimes
  - Often
  - Very frequently
- **5** : What is the reason for you doing this activity ?
  - This activity has been imposed to me
  - This activity has been suggested to me
  - I want to train myself

- **6** : What is your goal ?
  - I don't have any goal
  - Get the best final score
  - Having a good grade to my course
  - Having fun
  - Improving my coding skills
  - Learn to code a connected object
- **7** : Are you motivated in this activity ?
  - Not at all
  - Not very much
  - moderately
  - Yes
  - Yes, a lot
- **8** : How do you handle your time ?
  - Really badly
  - badly
  - I am neither good or bad
  - well
  - Very well
- **9** : Do you think you can reach your goal ?
  - Not at all
  - Not very much
  - moderately
  - Yes
  - Yes, a lot

  If question 6 was set to "I don't have any goal", we change the 9th question by the 6th.
- **10** : How have you handled your time ?
  - Really badly
  - badly
  - I am neither good or bad
  - well
  - Very well

- **11** : What do you think about your strategy in order to reach your goal ?
  - Really bad
  - bad
  - neither good or bad
  - good
  - Very good
- **12** : Have you reach your goal ?
  - Not at all
  - Not very much
  - moderately
  - Yes
  - Yes, a lot

  If question 6 and 9 was set to "I don't have any goal", we automatically set the answer to "I Totally disagree".

8.3 Github

All the project will be accessible at Xcale Master Thesis, we details here how to reproduce and use the notebooks, data and images to see our work.

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