International Journal on Advanced Science Engineering Information Technology

Vol.10 (2020) No. 4
ISSN: 2088-5334

Reading with Robots: A Personalized Robot-Based Learning Companion for Solving Cognitively Demanding Tasks

Azizi Ab Aziz[a,1], Hayder M.A. Ghanimi[a,2]

[a] *Human-Centred Computing Research Lab, School of Computing, Universiti Utara Malaysia, 06010 Sintok, Kedah, Malaysia*
E-mail:[1]aziziaziz@uum.edu.my; [2]hayder.alghanimi@gmail.com

***Abstract*— Soon, sociable companion robots will become indispensable for providing related support in our daily living and tasks. This paper provides process, design perspectives, and deployment of a reading companion robot (IQRA') that monitors the cognitive load level of a reader during demanding reading tasks and to provide support for readers to complete tasks. Current technological solutions only cover external design aspects of the application and have no adaptive mechanisms to deal with dynamics with the reader's perspectives and environment. Inspired by several theories from cognitive psychology domains, a computational model of the cognitive load was developed as a basis for reasoning and analytical purposes. This analytical ability provides the robot with a computational mechanism to reason in human-like manners and analyses of the functioning of observed conditions. This is essential in providing better-informed actions and intelligent analysis. Besides, the physical and software design of the robot and essential concepts in human-robot interaction are covered. Also, five evaluation constructs were chosen to evaluate the capability of our robot-based platform. These constructs are; 1) likeability, 2) perceived intelligence, 3) sociability, 4) social presence, and 5) cognitive load. The overall results from the pilot study support the practical usage of our proposed robotic solution.**

***Keywords*—companion robot; cognitive load modelling; personalized user system; personalized reading companion.**

I. INTRODUCTION

The cognitive load concept has been used to understand a large of instructional procedures, with special aims to alter the development of cognitive load eventually [1], [2]. For example, in the process of learning mathematical and scientific concepts, learners will try to solve some related forms of activities that aimed to improve different cognitive structures. However, some learners react differently with the problem due to cognitive obstacles [3]. In this construct, the cognitive obstacle prevents learners from understanding difficult concepts or from solving complicated technical contents and tasks. Without control and support, this will lead to the formation of cognitive load.

In this article, we are interested in providing the first step towards the deployment of a reading companion robot (IQRA') as an alternative to reduce cognitive load and improve the reading experience. Designing a reading companion robot based on cognitive load analytics is challenging. On the input side, this robot can observe the reader's basic cues to be used in a later step for assessing and monitoring the cognitive load level. As a result, the robot will intervene and help in human-like manners. Thus, the main contribution of our work is to provide an underlying model to design a reading companion robot based on a derived cognitive load model. Also, IQRA' was developed based on the research design perspective. Thus, IQRA aims to empower reasoning and analytics capabilities to comprehend the needs of users and its environment and providing related support based on the assessment of the situation. This article is organized as follows. First, we introduce important concepts in cognitive load as an underlying concept under the problem domain. Later, the human-robot interaction (HRI) notion used in this study is covered. Next, the hardware and software platform is described. Later, both quantitative and qualitative results from human experiments evaluation are discussed. Finally, a discussion and future direction of this work conclude this article**.** In this study, theoretical concepts in cognitive load are used as a basis to develop a reasoning mechanism for the robot.

Cognitive load can be defined as learning structures related to the interplay between long-term memory, knowledge skills, working memory, and consciousness with our information processing system. This concept provides a useful construct to understand the underlying process of intellectual tasks and the carrying capacity of cognitive abilities. [1]. In many conditions, experienced cognitive load is positively correlated to the overwhelming and unnecessary demands are imposed on a learner. This process made the normal task processing activities are becoming more complicated to be solved. [4]. Those demands are related to the unnecessary interferences of learners' environments and inadequate experience or resources to tackle given tasks or subjects. When learners can overcome cognitive load, they can harness their new abilities to acquire new skills faster without an overwhelming cognitive load level as it interferes with the development of new memories [2]. This piece of information may only be stored in long-term memory after being processed by working memory. However, there are limitations within working memory capacity and duration. If these limitations could be overcome, it will improve learning. In general, cognitive load can be categorized into three categories [5], namely; 1) Intrinsic Cognitive Load, 2) Extraneous Cognitive Load, and 3) Germane Cognitive Load, as presented in Fig. 1.

Firstly, the *intrinsic cognitive load* is something learners experience every time they learn something new. For example, when they learn something new, like a new method in mathematics, learners are not only learning how to decipher the problem, but also the primary mathematical operations and how they relate to each other. Without a proper approach, learners may be left confused, overloaded, and perhaps frustrated. Secondly, the *extraneous cognitive load* is something that leaners work tirelessly to reduce in their learning processes [3]. As an instance, any difficult topic learners want to understand; it comes with the right information that needs to be absorbed and understood. Thus, it requires different types of mediums that have their cognitive load. Also, this type of cognitive load is unintentionally misdirecting students with distracting information or makes a task more complicated than it needs to be [5].

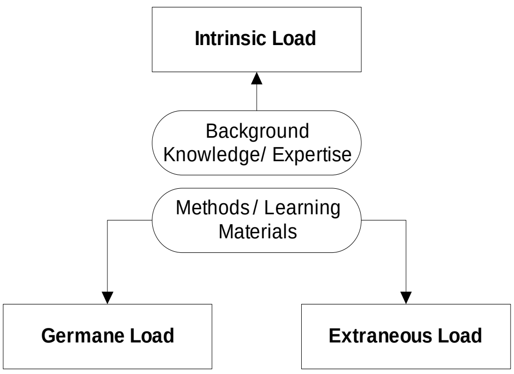

Fig. 1 Interplays within an intrinsic, extraneous, and germane load

Lastly, the *germane cognitive load* deals with pertinent and useful information absorption (related to the processing, construction, and automation of schemas) [2]. During this process, leaners begin to comprehend the new pieces of information and how they are related to each other. In this case, the germane cognitive load is needed to be optimized. While the intrinsic load is generally thought to be irreversible, technological solutions can influence extraneous and germane load. Through this, the negative effects of extraneous load and stimulate germane load can be minimized.

II. Material And Method

This section describes our proposed robotic platform named IQRA'. IQRA' is designed to receive input and display feedback from a group of various students in different academic programs at Universiti Utara Malaysia [6].

A. Human-Robot Interface

The general IQRA' user interface is developed to recognize some cues from readers and to deliver feedbacks to the readers through audio/video playback, social vocalization, and facial expression. Every aspect of its design is directed toward making the companion robot capable in providing subtle interactions and pieces of advice to support readers. Thus, it requires IQRA' have a rich enough support feedback repertoire for cognitive load support and a rich enough social interaction behavior to act upon them. As such, the human-robot interface design must address the following design principles:

- Real-time performance
- Readable social cues
- Self-motivated interaction
- Recognizing progress and success

For the real-time performance, IQRA' social interface must respond at interactive rates accepted by users as excessive latencies disrupt the social flow of human-robot interaction. When it comes to readable social cues, IQRA' must convey information as like humans as possible without requiring any special training. Self-motivated interaction allows IQRA' to exhibit proactive behaviors fueled by the computational model-based reasoning (analytical model). For recognizing progress and success, IQRA' is designed to have a mechanism to identify both properties. The computational model for cognitive load analysis extracts important measurements to be used as a basis for those properties. For example, by observing the formation of cognitive load in a real-time setting, IQRA is capable to predict potential load and later interfere with the process by providing necessary supports.

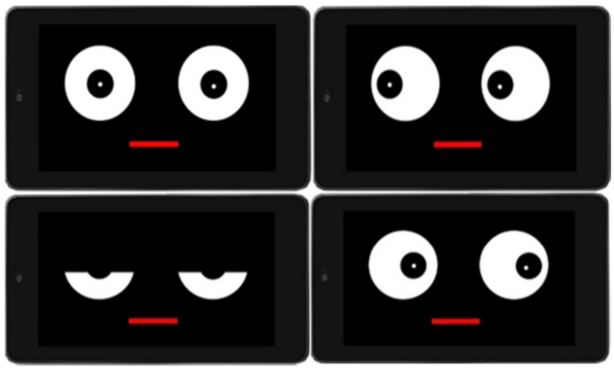

Fig. 2 IQRA' social interface animations

Fig. 2 depicts some cases of the designed robot's social interface based on animations where a believable social interface of IQRA' is generated. In the IQRA system, multiple robot social interfaces are running through each posegraphy synchronously, among others; *looking left*, *eyeblink*, *looking front*, *idle*, and *looking right*. Fig. 3 shows the posegraph for all the four installed social interface behaviors.

For example, the *Idle* mode is activated when no active gesture is being acted out. Therefore, the *Idle* animation moves subtly to give an impression of breathing, slightly moving the arm back and forth (or left to right for the robotic head). *Blink* mode is triggered randomly from six to 20 blinks per minute when the robot function is not occupied by some other activities. Another social interface animations, *Look Front*, *Look Left* and *Look Front* utilize the 2-dimensional Cartesian coordinates to provide a life-like movement akin to human social behaviors when interacting with each other. Those aforementioned social interface animations enhance the lifelikeness of the IQRA' along with the physical robot movements.

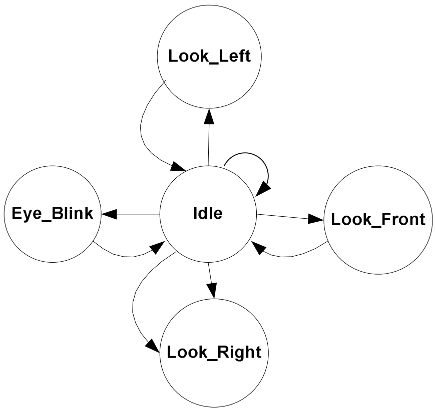

Fig. 3 IQRA' social interface posegraph

B. Concurrent Grounding Interaction Mechanism

To provide a concurrent grounding interaction mechanism for a robot (IQRA') to attain more fluid interactions, we have characterized the reader and robot as having a set of mutual parallel states. The principal of this grounding interaction mechanism is to provide a fluid interaction process by which the robot evaluates its own interaction goals in real-time and, therefore, to show commitment towards interactions.

Thus, the $InteractionGoal_{(U,R)}$ for user U and robot R is represented as the most desired interaction state the user intends to achieve in the future. This interaction state S is related to the current action of the robot a, the robot's state *Robot*, and the current robot's social cues *Cues*. The interplay between these attributes can be seen as below:

$$InteractionGoal_{(U,\,R)} \coloneqq argmax_{s\in \mathrm{States}}\, p(s \mid a, Robot, Cues)$$

In this study, the reader's goal is being updated through an analytic model (based on the cognitive load analysis component as in [8-9]). The result from this analysis only is evaluated to become adequately and mutually coherent with the robot when a definite criterion has been achieved. In our work, we use a real-value threshold φ, and $0 \leq \varphi \leq 1$.

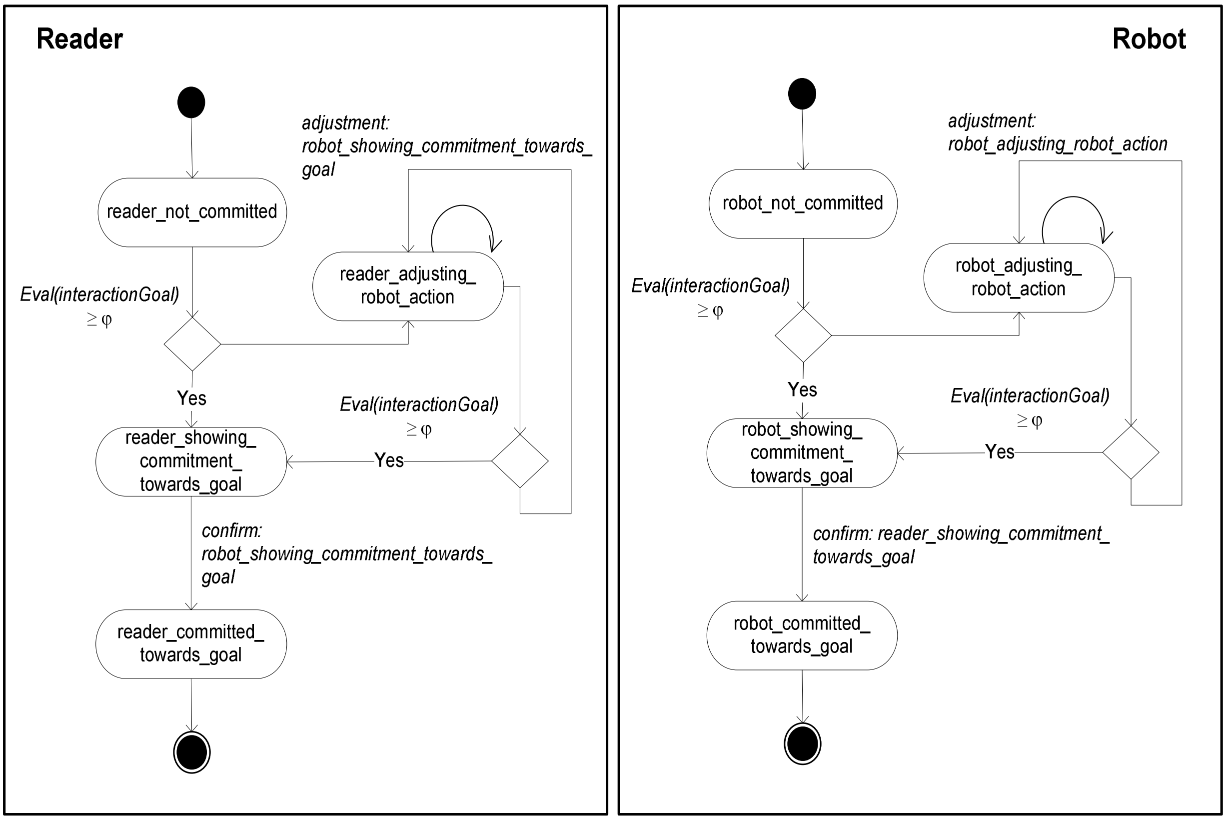

Fig. 4 State chart for a concurrent grounding interaction process

This criterion allows us to model the concurrent interaction process between a robot and reader without having explicitly to represent the entire probable dialogue states. Fig. 4 defines the grounding states and transition for a simple human-robotic dialogue system, which interprets a reader's feedback to carry out related actions.

C. Robot Social Greetings and Proxemics

Within typical human-to-human daily interaction, humans always include several imperative social cues such as non-verbal nuances, prosody, vocalizations, and physical distancing. From this standpoint, through properly enacted greetings to these nuances, it will guide a robot and people to participate in the interaction. This is due to the multidimensional and intuitive social rules that humans acknowledge it "as socially acceptable" must occur for the social interaction to take place (e.g., engaging, and natural). IQRA' is equipped with a set of social greeting behaviors to allow fundamental but seamlessly initial interactions with readers. These behaviors are related to the social science of greetings introduced by Kendon [9]. Table 1 shows these social greeting behaviors.

TABLE 1
IQRA'S SOCIAL GREETINGS BEHAVIOURS

Greetings Phases	**Behaviors**
Sighting and Decision to Greet	*Short Interruption, Passing Glance*
Distance Salutation	*Head Toss, Head Lower, Head Nod*
Transition	*Changes_Head_Orientation*
Final Approach	*Eye Change*
Close Salutation	*Verbal Greetings, Head Movement*

Within the IQRA's greeting process behaviors, readers adjust their interpersonal distance to acquire comfortable social spaces. This essence is important as humans tend to exhibit different behaviors towards each other based on four levels of social spaces. These social spaces (or known as proxemics), as shown in Fig. 5.

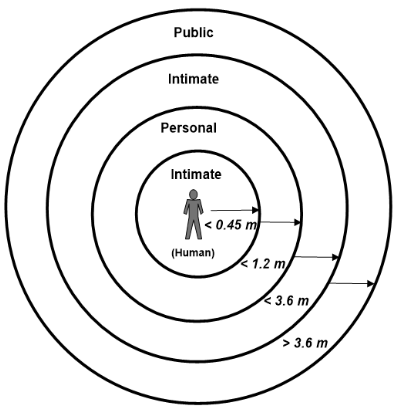

Fig. 5 Proxemics / Socially acceptance distance

Firstly, an intimate space exists when two or more people with a close relationship engage in communication while a personal space tends to be used by people in conversation who are comfortable with each other. This social space seems to be recognized useful for impersonal business as it allows people to know each other for formal interaction. Finally, a public space occurs for general (among crowd) presentations or when people avoid themselves from others.

Fig.6.Selected acceptance distance between IQRA' and readers socially

Coupled with social greetings, IQRA's socially acceptance distances are relevant in all phases. IQRA' utilizes both intimate and personal spaces as readers move progressively through zones and social greetings accordingly (as in Fig. 6).

D. Hardware and Robot Design

Overall, the software architecture for the IQRA' aims to minimize the required devices for ease of setting up the system and maximize the quality of the interaction with minimal latency in network communication in a real-world setting. IQRA' has gone through several iterations (design sprints) before be concluded that it has a sufficient capability for evaluating our core research questions. Hence, several design iterations were involved in exploring different configurations based on the results of our pilot study [6]. During this stage, a low-fidelity paper-based prototype was iteratively designed to serve as guidelines for our proposed robot-based platform. These design elements are related to the different hardware components, including the robot's arm and neck, robot social interface, motors positions, and its base to hold the physical components. Fig. 7 visualizes the fundamental evolution of the proposed robot.

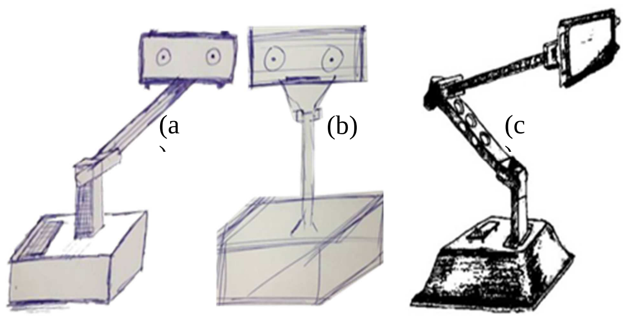

Fig. 7. Low-Fidelity Paper Prototyping ((a) first iteration, (b) second iteration, and (c) third iteration)

Upon the agreement for a final design of the robot, the solid modeling process was implemented to construct the physical robot. The design specification for IQRA' is up to 40 cm tall for a table or countertop set. As seen in Fig. 7, there is also a flexible touch-enabled input screen (based on ASUS 7" smart tablet powered by an Android platform) that allows data entry. Also, IQRA is powered by inexpensive servo controllers for fluid motion control as in Figure 8.

Fig. 8 Physical robot prototype

IQRA' has four degrees of freedom (DoF) to control the arm and neck movements by allowing each a full range of horizontal and vertical motions. To facilitate a fluid reader-robot interaction, the robot is equipped with input-output modalities that include motor outputs (servo and DC), speaker, touch screen, and mini-computer processor (Raspberry Pi). A schematic of the hardware components is presented in Fig. 9.

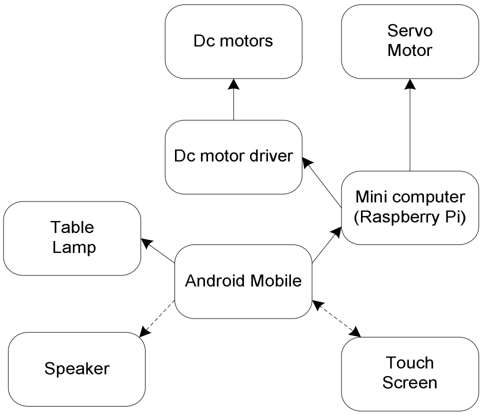

Fig. 9 Hardware components

The degrees of freedom for IQRA' are driven by DC and servo motors for accurate position control. Besides, the *SmartDriveDuo* 10 device is used together with Raspberry Pi to power both DC and servo motors. This motor driver is used to operate a medium power brushed DC motor for differential drives up to 30A peak (few seconds) and 10A continuously.

E. Computational Model of Cognitive Load Analytics

Theories in cognitive load concepts were used as a basis to develop a computational for cognitive load and reading performance. Fig.9 shows the conceptual constructs of the proposed model. Later, using *Network-Oriented Modeling* approach, the formal structure of the model was translated into a set mathematical specification (based on differential equations) to build temporal-casual network models. This causative modeling approach can be viewed either by a conceptual representation or by a numerical representation. A conceptual representation of a temporal-causal network model comprises representing (mental) states and connections between them that represent (causal) impacts of states on each other. These states are anticipated to have (activation) levels that dynamically change during the execution process. Also, those states are formed based on the following three notions:

- Connection weights characterize the strength of the connection.
- Combination functions aggregate the causal impacts of more than a state on one state (e.g., sum function).
- Speed factors represent the speed of change based on temporal effects (causal impact).

.

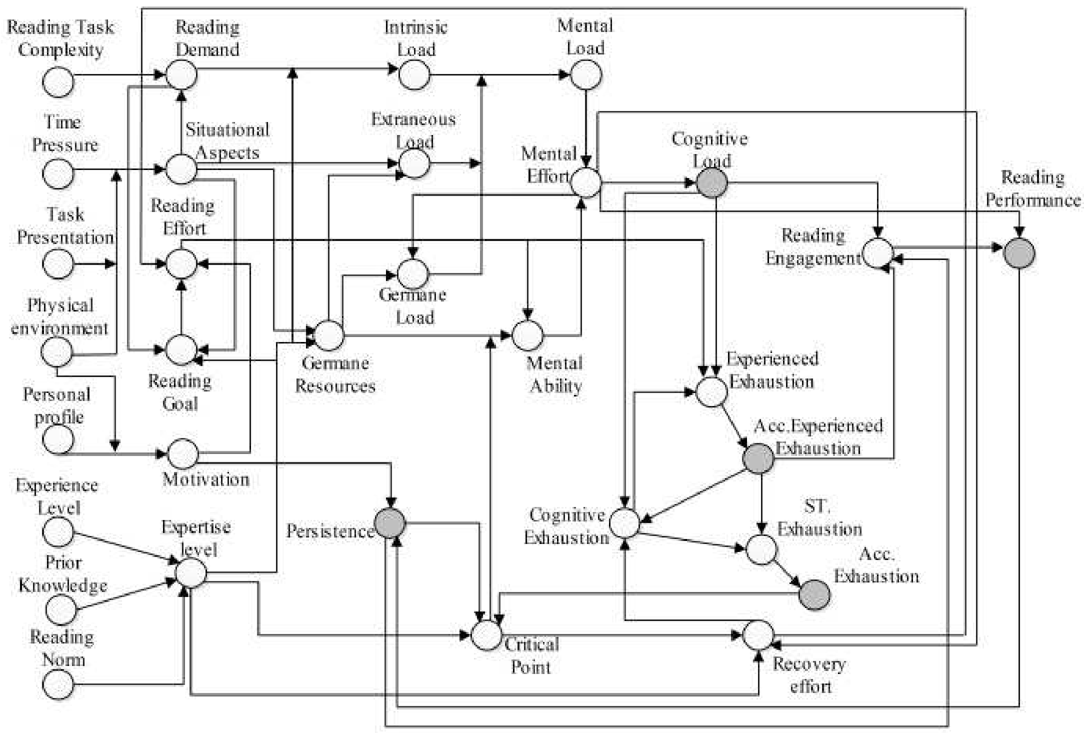

Fig. 10 Conceptual model of cognitive load and reading performance

After the conceptual representation was designed, those interrelated nodes (as in Fig. 10) are then with all nodes are designed to have values ranging from 0 (low) to 1 (high). This computational model involves several instantaneous and temporal relations, which are represented in differential equations. The general pattern underlying these dynamical relationships is as follows:

$$Y_A(t+\delta t) = Y_A(t) + \tau \;.\; \langle change\_expression \rangle .\; \Delta t$$

Here, the change of Y is specified for a time interval between t and $t + \delta t$, and τ are personal flexibility parameters that represent the speed of the cognitive load adjustment processes. Within <*change_expression*>, there are two cases that can be considered; *upward* and *downward* change expressions. These case are determined using the operator Pos(x), where Pos(x) = x when $x \geq 0$, else 0.

Using the formalized concepts, several relevant differential equations were generated as a part of the computational modeling process for the conceptualized cognitive load and performance model. Some examples of the generated differential equations are as follows. First, mental effort (*Me*) is represented by combining the effect of mental load (*Ml*) and mental ability (*Ma*).

$$Me(t)=(1-Ma(t)).Ml(t) \tag{1}$$

Cognitive Load (*Cl*) is primarily contributed to the accumulation of exposure towards previously encountered mental efforts.

$$Cl(t+\delta t)=Cl(t)+\beta_{CL}.[Pos(Me(t)-Cl(t)).(1-Cl(t)) -Pos(-(Me(t)-Cl(t)).Cl(t)].\delta t \tag{2}$$

Fig. 11 depicts the analytic result of the cognitive load formation for three different individuals (correspond to each personal profiles and conditions).

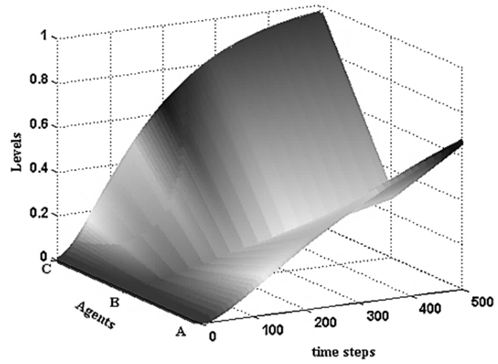

Fig. 11 Simulation Results from Cognitive Load Analytics

Using all defined formal specifications [10], an analytical model was established for exploration purposes, specifically to discover interesting patterns and traces that describe the behavior of the computational model related to cognitive load states. The advantage of using this approach compared to the "user-design" approach is due to its versatility and adaptive towards changes within environment and reader's needs.

F. *Software Design*

The main software system manages all input and output, sustains the general state of the interaction with the user, and handles the stream of interaction based on input from the user. The overall architecture is depicted in Fig. 12.

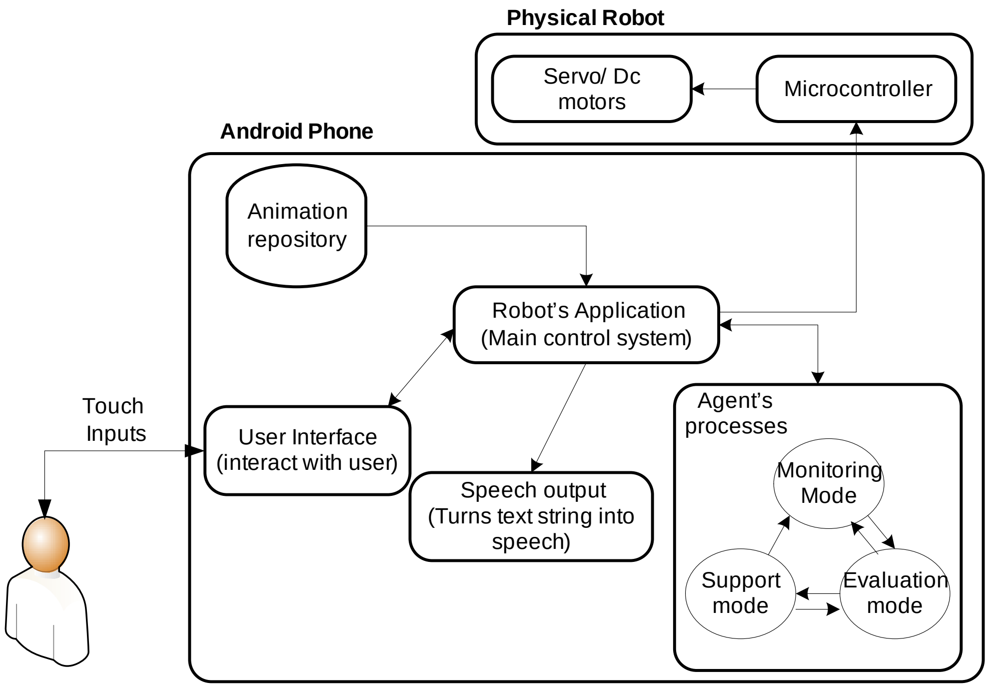

Fig. 12. Software components

The Android phone is the core of the robot's framework, which runs all computational analytic modules (i.e., monitoring, evaluation, and support) as well as externally communicates to the physical robot over socket interfaces. First, the *Main Control System* integrates all different programming classes such as social interface animations and motor controller in a seamless manner without any conflict. Second, the *Animated Social Interfaces* (from the *Animation Repository*) generate a believable anthropomorphic face to support a subtle interaction process between readers and a robot.

During the monitoring mode, IQRA' imports a set of animations from the repository and plays them on the smart-phone screen. Third, the motors controllers send motors positions over Socket to the Raspberry Pi system to direct fluid arms and head movements. Finally, the *User Interface* component allows a smooth human-robot interaction process through a customized touch interface to receive inputs from a user and show spoken text on the screen. Besides that, the robot user interface is customized to display and play learning materials as well.

III. Results And Discussion

This section covers the results from conducted experiments to assess the users' perceptions of their interaction with IQRA' and the outcome of this interaction in reducing cognitive load.

A. Methods

In this study, several undergraduate students from the School of Computing, Universiti Utara Malaysia were recruited to participate in Data Structure and Algorithm Analysis reading task (e.g., Tower of Hanoi puzzle). They were given an hour with the help of IQRA'. These students were selected based on selected criteria such as to have below-average performances in this subject (i.e., scored low grade). The reason behind these criteria is to ensure that they will experience a high cognitive load level during the experiment. Moreover, all of them are from a homogenous group to eliminate any possible experimental bias. The data collection instruments that were developed based on the research survey approach were closed-ended questions, and a semi-structured interview was used to capture compelling insights from respondents.

Consequently, the demographic information of the respondents and system usability (adopted from [11]) were measured. In this study, the 7-points semantic differential scale was used to measure the user's impression towards using a reading companion robot where different aspects were measured (adopted from [12]). These aspects are; 1) *likeability*, 2) *perceived intelligence*, 3) *sociability*, and 4) *social presence*. Also, the cognitive load was measured using the 7-points Likert scale questionnaire (adapted from [13]). Moreover, questions related to the *Desire to Continue* using the system, *Satisfaction* with the support given while using the robot, and *Motivation* were obtained. Towards the end of the experiment, respondents who participate in the study were given refreshments (drinks and snacks) and a special gift as a token of appreciation.

B. Quantitative Results

Ten students were recruited into the experiment (eight males and two females), aged 19-24 (Mean 21.5, SD=1.4) years old and most of them are Malaysian (entry requirement through Matriculation, STPM or Diploma). Upon the completion of the experiment, data related to the usability was collected, and it found that the level of functionality of the robot is quite high (Mean=6, SD=0.47). This result indicates that the proposed reading companion robot is easy to be used and not complex. For the *Related to Likeability* and *Perceived Intelligence*, the results have shown that participants like the robot (Mean=5.74, SD=0.65) and perceive the robot as an intelligent companion/sidekick (Mean= 5.48, SD=0.51). These results for both constructs are depicted in Fig. 13.

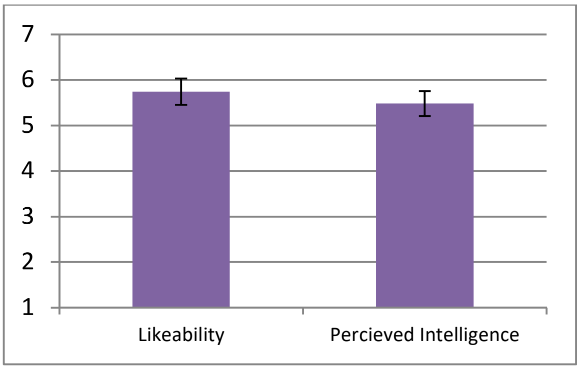

Fig. 13 Results for likeability and perceived intelligence

We have also measured the sociability construct, and the results have shown that participants perceived IQRA as a system that can perform social behaviors with Mean=5.43 and SD=0.65. Besides, an almost similar result has been observed in the social presence construct (Mean=5.12, SD=0.627). These results are shown in Fig. 14.

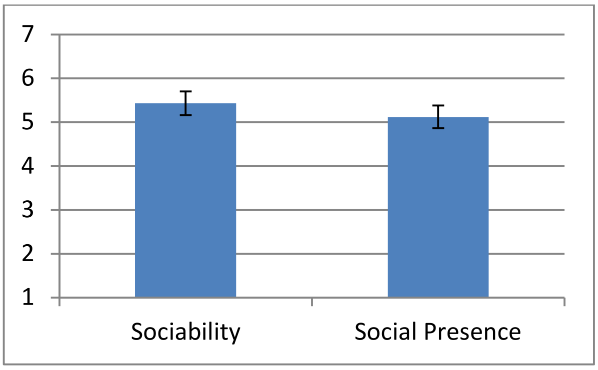

Fig. 14 Results for sociability and social presence

For the cognitive load measurement, the respondents were prompted within three specific periods to evaluate the overall level of cognitive load (by rating the perceived task difficulty level). Fig. 15 visualizes the analysis results of cognitive load for these three different time points. From Fig. 15, it shows that an average cognitive load level participant has experienced to solve the assigned task has been decreasing gradually. It means the participants at the end of the experiment were experiencing a low-level of cognitive load compared to the load they have encountered at the time point #1.

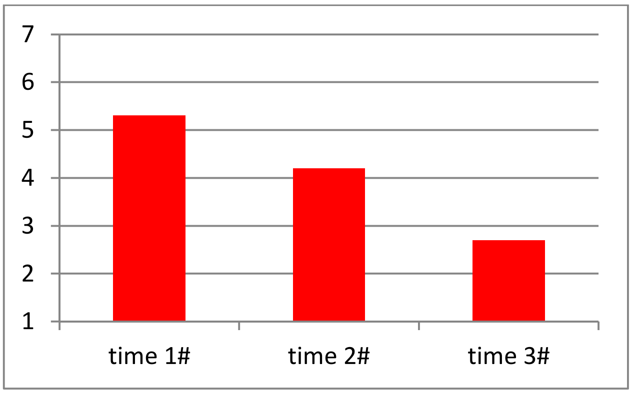

Fig. 15 Results of cognitive load at different time points

Consequently, these findings provide a piece of vital evidence to show that helped of the reading companion robot can reduce the experienced cognitive load.

C. Qualitative Results

In addition to the quantitative experiments, we recorded all sessions and post-session interviews. The overall responses are aligned with our quantitative analysis. Examples of the participants recorded opinions are as follows:

"yes, I found it interesting, and I would like to have it. It is friendly and helped me to figure out the task… It motivates me to keep the workup, and I like this."

"yes, It is nice and friendly and helpful…I would like to use it more. It helps me when I felt…I cannot solve the task. I like the way it praised me, awesome!"

"of course, I can use it, especially to solve my assignments. I am satisfied with the supports it showed to me! Yes, it motivated me like a friend. I like it."

"Absolutely, I want to continue using it to see its potentials…it seems intelligent. Yes…yes. I am delighted. Indeed. I even smiled when it praised me. I think it knows how to motivate the students."

IV. Conclusion

In this article, the design of a reading companion robot that supports readers was proposed. The designed robot incorporates a computational model of the functioning of the cognitive load, physical and software modules. In addition, the robot shows a clear, encouraging tool that can be helpful to be a digital sidekick during reading and solving challenging tasks. More specifically, we sought behavioral characteristics that imperative to design a reading companion robot such as likeability, perceived intelligence, and sociability. Moreover, the implementation of the proposed computational model could be extended in another domain, as it is a generic concept and can be plugged in with some minor alteration. Besides, it is expected that this work can stimulate the creation of other similar robotic systems that can aid humans in solving real-world problems.

Acknowledgment

This work was funded by the Universiti Utara Malaysia Postgraduate Research Grant and RACE grant (by the Ministry of Higher Education, Malaysia). The authors would like to express thanks to Associate Profesor Dr. Faudziah Ahmad (a former member in this research group) for her guidance and assistance.

References

[1] J. Sweller, P. Ayres, and S. Kalyuga, *cognitive load theory*. New York: Springer, 2011.

[2] F. Paas, A. Renkl, and J. Sweller, *Cognitive Load Theory: A Special Issue of educational Psychologist*. Taylor & Francis, 2016.

[3] R. Antonijević, "Cognitive Activities in Solving Mathematical Tasks: The role of a Cognitive Obstacle.," *Eurasia J. Math. Sci. Technol. Educ.*, vol. 12, no. 9, 2016.

[4] H.-H. Choi, J. J. G. van Merriënboer, and F. Paas, "Effects of the physical environment on cognitive load and learning: towards a new model of cognitive load," *Educ. Psychol. Rev.*, vol. 26, no. 2, pp. 225–244, 2014.

[5] N. H. Jalani and L. C. Sern, "The Example-Problem-Based Learning Model: Applying Cognitive Load Theory," *Procedia-Social Behav. Sci.*, vol. 195, pp. 872–880, 2015.

[6] H. Mohammed, A. A. Aziz, and R. Ahmad, "Exploring the need of an assistive robot to support reading process: A pilot study," in *2015 International Symposium on Agents, Multi-Agent Systems and Robotics (ISAMSR)*, 2015, pp. 35–40.

[7] H. M. A. Ghanimi, A. A. Aziz, and F. Ahmad, "An Ambient Agent Model for a Reading Companion Robot," in *Information Systems: Proceedings of the Computational Intelligence in Information Systems Conference (CIIS 2016)*, 2017, pp. 94–106.

[8] H. M. A. Ghanimi, A. Ab Aziz, and F. Ahmad, "Designing an Intelligent Support Model of a Reading Companion Robot," in *Intelligent Environments 2017: Workshop Proceedings of the 13th International Conference on Intelligent Environments*, 2017, vol. 22, p. 131.

[9] A. Kendon, *Conducting Interaction: Patterns of Behavior in Focused Encounters*. Cambridge University Press, 1990.

[10] J. Treur, *Network-Oriented Modeling: Addressing Complexity of Cognitive, Affective and Social Interactions*. Springer International Publishing, 2016.

[11] J. Treur, "Dynamic modeling based on a temporal–causal network modeling approach," *Biol. Inspired Cogn. Archit.*, vol. 16, pp. 131–168, 2016.

[12] H. M. A. Ghanimi, A. A. Aziz, and F. Ahmad, "An Agent-Based Model for Refined Cognitive Load and Reading Performance in Reading Companion Robot," *J. Telecommun. Electron. Comput. Eng.*, vol. 9, no. 3–5, pp. 55–59, 2017.

[13] J. Brooke, "SUS-A quick and dirty usability scale," *Usability Eval. Ind.*, vol. 189, no. 194, pp. 4–7, 1996.

[14] C. Bartneck, D. Kulić, E. Croft, and S. Zoghbi, "Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots," *Int. J. Soc. Robot.*, vol. 1, no. 1, pp. 71–81, 2009.

[15] A. Schmeck, M. Opfermann, T. van Gog, F. Paas, and D. Leutner, "Measuring cognitive load with subjective rating scales during problem solving: differences between immediate and delayed ratings," *Instr. Sci.*, vol. 43, no. 1, pp. 93–114, 2015.