Design of a Physiology-Sensitive VR-Based Social Communication Platform for Children With Autism

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***Abstract*— Individuals with autism are often characterized by impairments in communication, reciprocal social interaction and explicit expression of their affective states. In conventional techniques, a therapist adjusts the intervention paradigm by monitoring the affective state e.g., anxiety of these individuals for effective floor-time-therapy. Conventional techniques, though powerful, are observation-based and face resource limitations. Technology-assisted systems can provide a quantitative, individualized rehabilitation platform. Presently-available systems are designed primarily to chain learning via aspects of one's performance alone restricting individualization. Specifically, these systems are not sensitive to one's anxiety. Our presented work seeks to bridge this gap by developing a novel VR-based interactive system with Anxiety-Sensitive adaptive technology. Specifically, such a system is capable of objectively identifying and quantifying one's anxiety level from real-time biomarkers, along with performance metrics. In turn it can adaptively respond in an individualized manner to foster improved social communication skills. In our present research, we have used Virtual Reality (VR) to design a proof-of-concept application that exposes participants to social tasks of varying challenges. Results of a preliminary usability study indicate the potential of our VR-based Anxiety-Sensitive system to foster improved task performance, thereby serving as a potent complementary tool in the hands of therapist.**

***Index Terms*— Anxiety, autism, physiology, virtual reality.**

I. Introduction

AUTISM spectrum disorder (ASD) refers to a lifelong pervasive development disorder characterized by impairments in communication and social interactions [1]. Such deficits often restrict one from achieving adaptive independence, leading to enormous costs across the lifespan [2]. With prevalence rate of 1 in 150 in India [3], 1 in 68 in United States [4], 1 in 64 in United Kingdom [5], effective treatment of ASD is a pressing clinical and public health issue. Faced by such a critical need, conventional observation-based techniques (administered by expert therapists) are widely practiced with evidence of improved social communication skills [6]. However, there are potent barriers related to accessing and implementing such individualized, intensive intervention services e.g., limited access to and availability of appropriately trained professionals, lack of available data suggesting intervention that might be appropriate to a specific child, and exorbitant costs of one-to-one intervention sessions [7]. Researchers are now employing technology to develop more accessible, quantifiable, intensive and individualized intervention for addressing core deficits related to ASD [7]. Thus development of an intelligent system that can objectively identify one's affective states and adapt itself targeted to the specific child is critical. This can pave the way towards development of an individualized, intensive, and cost-effective ASD intervention tool.

Many studies have investigated application of technology-assisted tools, e.g., computer technology [8], Virtual Reality (VR) [9], and robotic systems [10] for adolescents with autism. With rapid progress in technology, it is argued that specific computer and VR-based applications can be harnessed to provide effective intervention for individuals with ASD [8] [11]. In our present work we chose VR, because of its malleability, controllability, modifiable sensory stimulation, individualized approach, safety, simplified but explorative training environment due to potential reduction of problematic aspects of human interaction particularly during initial skill training [12]. However, VR should not be considered as an isolating agent, because dyadic communication between a child and VR environment can lead to triadic communication including a clinician, caregiver, or peer and in due course potentially accomplish the intervention goals of developing social communication between the child with ASD and another person [13] [14]. Since VR mimics real environments in terms of imagery and contexts [12], it may offer efficient generalization of skills from VR environment to real world [15]. In our present research, the VR environment refers to the visualization developed to replicate a social communication scenario.

The currently available VR environments as applied to assistive intervention are designed to chain learning via aspects of performance alone (i.e., correct, or incorrect) thereby limiting individualization of application [15]. While working with individuals with ASD, expert therapists/interventionists often individualize their intervention services for floor-time-therapy [16]. Thus, to foster effective social communication skills, the VR-based system should intelligently adapt itself to a user's affective states with high degree of individualization [17].

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In fact, in conventional intervention settings, the therapist/interventionist often monitors the participant's affective state in addition to task performance to adapt her intervention strategy. The therapist's expert eyes pick up the participant's affective cues from facial expression, vocal intonation, gestures, postures, etc. However, adolescents with autism often possess deficits in explicit expression of their affective state that pose limitations on traditional observation-based techniques [18]. Researchers have been studying the potential of other modalities, e.g., physiological signals that can be mapped to one's affective state. Studies show that physiological signals can be evoked by different amounts in the presence of VR environments [19] and transition from one affective state to another is accompanied by dynamic shifts in indicators of Autonomic Nervous System activation [20]. In addition, physiological signals being continuously available and not directly impacted by communication deficits, may offer an avenue for recognizing one's affective state that is less obvious for humans but easily decipherable by computers. Here we chose anxiety as the target affective state, because, anxiety is a common concern in clinical samples with autism [13] and has adverse effects on an educational training. Also, anxiety plays an important role in human computer interaction that can be related to performance, challenge, and ability of the user [21].

Given the importance of monitoring one's anxiety, literature indicates physiology-based biomarkers of one's anxiety. For example, one's heart rate increases, tonic activity of skin conductance increases and skin temperature decreases with increase in one's anxiety [22] [23].

The primary goal of our research was to develop a VR-based technology with potential relevance to ASD intervention. Specifically, in this work we attempted to create a tool that could 1) allow real-time measurement of one's performance and associated physiological indexes that can be mapped to one's anxiety while interacting with VR-based social communication task; and 2) adapt the VR-based tasks based on the inferences regarding anxiety predicted from physiological indexes and performance. Realization of such a technology may pave the way for intensive, intelligent, and individualized intervention paradigms that can offer individualized feedback and reinforcement strategies during VR-based social skill training tasks. Also, this can help to identify at least some of the elements of social interaction that can cause anxiety among these individuals. This intelligent system can be adaptive to one's predicted anxiety in controlled environments, thereby reinforcing skills in core domains gradually but automatically, and in turn could be applied to a large class of potential ASD intervention paradigms.

Our paper is organized as follows. Section II presents system design. Section III discusses the method used and Section IV presents the results of a usability study. Section V summarizes the contribution of present work and scope for future research.

II. System Design

In our present research, we designed a usability study as proof-of-concept application, to expose participants to our

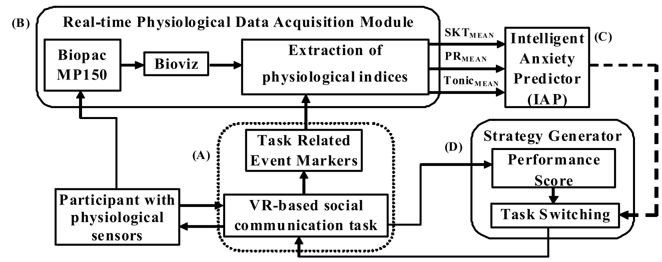


Fig. 1. Block schematic of Adaptive VR-based systemsNote: Biopac MP150: Data acquisition device; Bioviz: Handshake module; SKT$_{MEAN}$, PR$_{MEAN}$, EDA$_{MEAN}$ refers to mean values of Skin Temperature, Pulse Rate and Electrodermal activity, respectively.

VR-based adaptive systems configured as Anxiety-Sensitive (AS) and Performance-Sensitive (PS) systems. Our AS system offered tasks of varying challenges to the participants based on their performance and their anxiety level predicted from their physiological indexes. In contrast, our PS system offered tasks of varying challenges based only on the participant's performance. Also we acquired physiological signals for offline analysis. Our aim was to understand the implication of interaction with our AS and PS systems. Both of these systems comprised of four sub-modules, i.e., (A) VR-based social communication (B) Real-time physiological data acquisition (C) Intelligent Anxiety Predictor (IAP) and (D) Strategy Generator modules. Fig. 1 shows the schematic of our AS system. Unlike AS, the Strategy Generator module of PS system 1) does not include the IAP module output (shown dotted and discussed in Section II-D. 1) and 2) has Task Switching unit with only performance score as input (Fig. 1).

A. Design of VR-Based Social Communication Task

We used desktop-based VR applications [12] instead of the immersive type for increased accessibility, affordability and reduction of sensory burden along with disorientation. Here, we present the design of VR-based social communication task platform that projected social situations to the participants in the form of social stories. Social stories are short stories that describe a particular social situation in a structured and consistent manner [22]. Social stories have been shown to be an effective way of addressing deficits in social communication skills for individuals with ASD [24]. Since autism is characterized by deficits in imagination, use of context-relevant imagery can be useful to impart skill training to this target population [25]. In our present research, we have used commercially-available Vizard platform (from Worldviz Inc.) to design 24 social stories (12 each for AS and PS) presented through realistic context-relevant VR environments, to expose our participants to social situations.

The Vizard platform comes with a restricted database of social situations and virtual characters. We designed context-relevant social situations e.g., classroom, park, hotel etc., using Google SketchUp and later exported these to Vizard platform. For our present research, we selected a number of 3D character (avatar) faces from an available database that was created by using 2D front and side photographs of teenagers' faces, and subsequently these images were mounted on avatar heads to be used for our study. In order to make the faces look Indian, we changed the skin complexion, hair color, eyebrow color, etc., before using these modified faces for survey. A survey on these designed faces while depicting emotional expressions (happy, angry and neutral) was conducted among 14 undergraduate students (mean (std. dev.) age= 21.4 (3.6) yrs). We adopted the survey technique similar to another study where rating from typically developing (TD) counterparts were considered for the survey for selecting avatar faces [26]. The survey questions were designed to rate the faces on the valence and arousal aspects using a five point scale. Additionally, a question was also asked to understand whether the faces looked Indian, using a two point scale. Based on the survey, we estimated an overall rating for our designed faces (for details please refer to our companion paper [22]). Subsequently we chose faces whose facial emotional expressions, as interpreted by the viewers, matched closely to that intended by the designer and also looked like Indian. Based on the survey, we chose six avatar faces (three each for male and female). Additionally, our avatars were capable of gesturing, blinking, moving dynamically in context-relevant VR environments, and speaking in a lip-synched manner with pre-recorded audio files. The audio files were created from voices of age-matched volunteers who were recruited from the neighborhood. The faces used in our study were morphed to display happy and angry emotions. Our VR-based social communication tasks were categorized into two sub-tasks, namely, Social Interaction Task-I (SIT-I) and Social Interaction Task-II (SIT-II), with SIT-II following SIT-I. These were designed to offer varying challenges (i.e., Difficulty Levels DLI-IV) to the participants. In SIT-I, the participant was asked to interact with the social communicators (virtual characters) and instruct one of the characters to navigate the VR environment while following social norms and etiquettes. The SIT-II exposed the participants to subtle emotion-related aspects of social communication.

1) Design of SIT-I Sub-Task: In SIT-I sub-task, the participant interacted with a VR environment e.g., classroom, restaurant, park, etc. Initially, a virtual character (henceforth named as Avatar1) introduced herself with brief description of the environment where she was standing. Then she introduced her friend (henceforth named as Avatar2). The Avatar2 served as a facilitator and asked him navigation-related questions to which the participant responded by selecting his option choice from a menu-driven interface. In turn, Avatar2 responded to the participant by navigating through the VR environment. For example, let us consider a park scenario (Fig. 2). First, the Avatar1 introduced herself followed by a brief description of a crowded park and the different play items at the park, e.g., see-saw, slider, etc. After this, the Avatar1 introduced the common friend, Avatar2 who interacted with the participant and navigated the environment on the participant's behalf. Then Avatar2 asked context-relevant questions related to the play items to the participant. For example, one question was "Which play item would you like me to choose?" Our system then cued the participant with the option choices along with a view of the entire park comprising of different play items, e.g., see-saw, slider, turn-wheel, etc. (depending on task difficulty).

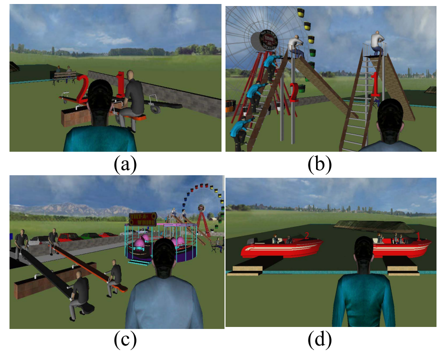


Fig. 2. Screenshot of an example of SIT-I.

Let us consider a scenario where only the see-saw was available for playing. Our system offered three menu-driven option choices audio-visually to the participant. For example, the options were: 1. Take a seat on the see-saw 2. Run around in the park and 3. Go back home without playing. The participant was asked to respond to 1, 2, or 3, using a number keypad placed in front of him. Based on the participant's response, Avatar2 navigated the environment to complete the task. If option 1 was chosen, the Avatar2 walked towards the see-saw. In case option 2 was chosen, Avatar2 reminded the participant that she might hurt herself if she ran around in the crowded park. For option 3, Avatar2 told the participant that it might not be a good idea to miss the opportunity by leaving the park without playing. Now, if the participant chose to play the see-saw, a social situation with two see-saws [Fig. 2(a)] was offered. One of the see-saws had someone sitting at one end and the other completely unoccupied. It was expected that one would choose the partially occupied see-saw following social etiquettes e.g., asking the occupant (at the other end) about his willingness to play together. In case the participant chose the empty see-saw, Avatar2 informed him that she would need a friend to play on the see-saw and it would be great if she was asked to make friends with the person sitting at the other end of the see-saw. A maximum of two attempts were allowed for each question. In case of inappropriate option choice by the participant, even in second attempt, Avatar2 informed the appropriate action that was expected to be made by the participant during the previous scenario. Then our system presented the next question.

For SIT-I sub-task, the task difficulty was decided based on the extent of social interaction required by the participant to complete a task in a social situation. The Avatar2 asked two context-relevant (CR1 and CR2) and one navigation-related (NR) question to the participant. For example, in DLI task, the participant was exposed to a very sparsely crowded park environment having play items with no/less interaction required [Fig. 2 (a)] by the participant. The CR1 question was "Where do you think that I am standing?" with "park" as one of the options. The CR2 question was "What are the play items at the park?" and the NR question was "Which play item would you like me to choose?" In DLII task [Fig. 2 (b)], the participant was exposed to a park scenario where some of the play items were occupied, and others were empty. The CR1 and CR2 questions asked in DLII were similar to those in DLI. However, for DLII task, the NR question was designed to make the participant think on certain aspects of social etiquettes, such as, choosing Slider2 instead of an over-crowded Slider1 [Fig. 2 (b)] to avoid commotion. In DLIII task [Fig. 2 (c)], the participant was exposed to a heavily crowded park environment where the participant was expected to choose a play item from among the available fully or partly occupied play items. For the partly occupied play items, three options e.g., "quietly wait aside for the play item to be completely empty," "show anger and shout while waiting aside till the play item was completely empty," and "start playing" were provided. The third option required the participant to choose a partly occupied play item and was expected to interact with other occupants on the play item. Thus the participant had to be aware of social etiquettes, e.g., ask permission from the occupants at the play items to play. Thus, in DLIII, added to CR1 and CR2 questions (similar to DLI), there was NR question that was designed to make the participant aware of social norms to be followed while navigating the environment. In DLIV task [Fig. 2 (d)], the participant was exposed to an over-crowded park where all the play items were completely occupied. The participant was given a chance to explore the other attractions in the park, e.g., boat riding. Here, added to CR1 and CR2 questions, the VR environment was designed in a manner that to respond to NR question, the participant needed to change his plan after inference from available facts. For example, the participant had to ask Avatar2 to do boat riding instead of playing with other over-crowded play items in near vicinity.

2) Design of SIT-II Sub-Task: The SIT-I was followed by SIT-II sub-task. In SIT-II, Avatar1 narrated her experience with context-relevant facial emotional expression, while visiting a social environment similar to that in SIT-I. The participant was exposed to some of the subtle aspects of social communication, e.g., facial emotional expression, looking pattern, etc. of the social communicator (Avatar1). The participant was asked to watch and listen to Avatar1 and respond to the questions asked by Avatar1 at the end of the narration. The difficulty level of SIT-II sub-task was based on the type of questions asked, e.g., context-relevant (CR), projected contingent (PC), emotion recognition (ER) and reporting on one's own feeling (RF). The CR questions were simple and direct questions addressing the contexts that were referred by Avatar1 during her narration. The PC questions required one to deduce certain facts mentioned in the narration, before responding to the question. The response to ER questions required the participant to recognize the emotions exhibited by Avatar1. Appropriate response to RF question required the participant to feel the situation from the Avatar1's perspective. These questions were designed with an aim to address some of the core social communication-related deficits of individuals with autism. Specifically, ER and RF questions were included in tasks of higher difficulty levels since these questions are often related to critical and major communication issues for individuals with autism. Fig. 3 (a) shows Avatar1 standing outside a park (visited during SIT-I sub-task) and narrating her experience with a happy face. Fig. 3 (b) shows a snapshot of the SIT-II sub-task with a menu-driven interface used by the participant to respond to Avatar1's question. In this sub-task, the CR, PC, ER, and RF questions were "where did I go?"; "what do you think that I would have done if the park was crowded?"; "how was I feeling while narrating my experience to you?" and "how would you feel if you also had a similar experience?" respectively.

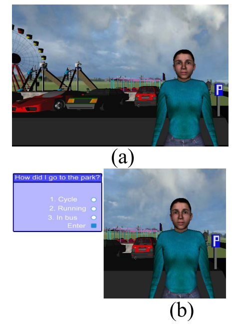


Fig. 3. Screenshot of an example of SIT-II.

To summarize, in our SIT-I sub-task, the Avatar1 introduced herself and her friend Avatar2 who navigated the VR environment in response to participant's option choices. The SIT-I was followed by SIT-II sub-task in which the participant was expected to watch and listen to Avatar1 narrating her personal experience accompanied with context-relevant facial emotional expression while moving dynamically through the VR environment. In turn, this was followed by the participant's response to questions (CR, PC, ER, RF) asked by Avatar1. In order to avoid the participant's feeling of monotony while interacting with virtual characters in SIT-I and SIT-II sub-tasks, we have used two virtual characters (Avatar1 and Avatar2) for our preliminary study.

B. Real-Time Physiological Data Acquisition

While our participants interacted with VR-based systems, their Pulse Plethysmogram (PPG), Electrodermal Activity (EDA) and Skin Temperature (SKT) signals, were acquired by Biopac MP150 (from Biopac Systems Inc.) operated in wireless mode with sampling frequency of 1000 Hz. The acquired signals were processed to extract three physiological indexes e.g., mean pulse rate (PRMEAN), mean skin temperature (SKTMEAN), and tonic mean (TonicMEAN) synchronized with VR-based task propagation (for details on feature extraction please refer our companion paper [22]).

We chose the physiological signals (e.g., PPG, SKT, and EDA), since studies show that these signals can be measured easily and non-invasively, and can be used as efficient anxiety markers [23]. Specifically, the autonomic nervous system that includes sympathetic and parasympathetic branches, is activated during anxiety state to mobilize appropriate behavioral responses to stressful stimuli [27] with anxiety being almost unanimously characterized by sympathetic activation [28]. In our study, we have used Pulse Rate (PR), Skin Temperature (SKT) and Electrodermal activity (EDA) as anxiety predictors. In fact, for PR, studies show that the sympathetic nervous system (SNS) has excitatory effect on cardiac function, thereby increasing one's heart rate. Again, for SKT, arousal of SNS generally results in vasoconstriction [27] that

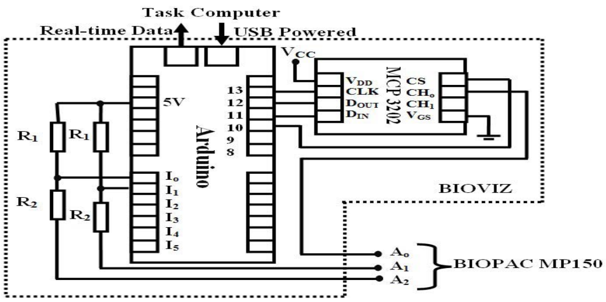


Fig. 4. Circuit Diagram of BIOVIZNote: I_o–I_5 indicates the analog inputs of Arduino.,R_1 = 2.5k ohms, R_2 = 2.5k ohms, A_0-A_1 indicates input from BIOPAC MP150, CH_0 and D_{OUT} refer to the input and output of MCP3202.

in turn affects one's cutaneous micro-circulation to bring about changes in skin temperature measured from transient changes in one's fingertip temperature. Also, a high correlation between the level of sympathetic activity and changes in EDA on account of perspiration has been reported [27].

In our study, we acquired PPG, SKT, and EDA signals from one's middle finger, thumb and the index and ring fingers of non-dominant hand. The participant's physiological signals were acquired in real-time and in a synchronized manner along with VR-based task progression by using Arduino-based Biopac-Vizard hardware interface (Bioviz, henceforth) designed in-house. The Biopac MP 150 hardware comes with its Acknowledge 4.3 Software for acquiring and processing physiological signals in standalone mode. In our study, we acquired one's physiological signals in real-time using the MP150, and then these signals were routed through our custom-designed Bioviz [SKT, PPG, and EDA signals connected to A0, A1, and A2 terminals of Bioviz (Fig. 4)] to extract relevant physiological indexes that in turn were fed to an Intelligent Anxiety Predictor module (discussed in Section II-C) to predict one's anxiety level. The Bioviz comprised of an Arduino Uno [29] along with an external 12 bit Analog-to-digital (ADC) converter (MCP3202) for the comparatively slow-varying EDA signal.

The Bioviz ensured time-synchronized acquisition of physiological signals. Each task trial consisting of SIT-I and SIT-II sub-tasks allowed approximately 1.5 min for SIT-I and 1.75 min for SIT-II (on an average) for acquisition of participant's physiological signals. An interval of approximately 1 min was allotted for our system to pre-process and filter the acquired raw physiological signals, compute the physiological indexes and the performance score before presenting the feedback and the next task trial using the task switching rationale. During this interval, an intermediate white screen was displayed on the task computer on which the feedback was subsequently presented. The idea was to provide some time (approximately 1 min) to the participant to relax and get prepared for the next task.

C. Intelligent Anxiety Predictor (IAP)

While the participant interacted with VR-based tasks, the mean value of his physiological indexes, e.g., PRMEAN, TonicMEAN and SKTMEAN were computed in a synchronized manner along with VR-based task progression.

TABLE I
ANXIETY PREDICTED FROM PHYSIOLOGICAL INDEXES

Predicted anxiety level	%Δ from Previous		
	$\%\Delta SKT_{MEAN}$	$\%\Delta PR_{MEAN}$	$\%\Delta Tonic_{MEAN}$
1	$-0.5<\%\Delta<0$	$0<\%\Delta<1.5$	$0<\%\Delta<50$
2	$-1.5<\%\Delta<-0.5$	$1.5<\%\Delta<4$	$50<\%\Delta<100$
3	$\%\Delta<-1.5$	$4<\%\Delta$	$100<\%\Delta$

These physiological indexes were then fed to fuzzy-logic based Intelligent Anxiety Predictor (IAP) units for predicting one's anxiety level. Literature review indicates use of fuzzy-logic in wide variety of applications related to control engineering, image processing, industrial automation and robotics [30]. Fuzzy-logic enables deduction of facts extracted from available interpretable knowledge and hence often serves as a promising classification tool [31]. Here we chose Fuzzy-logic, since this allows data uncertainty [32]. The fuzzy-logic based IAP unit used in our study comprised of three sub-units, namely, fuzzification, inference engine and defuzzification units [32]. Fuzzification unit maps crisp input physiological signal values on a 0 to 1 scale using a set of membership functions. The inference engine unit makes inference based on physiology-based mapping rules. The defuzzification unit finally provides the crisp output values of 1, 2, or 3. Note that the discretization through use of numeric values (Table I) is a first approximation towards quantifying anxiety. Our system is not limited to three levels of quantification–a much finer resolution is possible depending on the task requirement. The output numeric value from each IAP unit was then summed up to predict the anxiety level as "high" or "low." If the cumulative sum of quantification scores from the three IAP units was ≥ 6 (out of maximum of 9) then the anxiety was labeled as "high," else, "low."

D. Strategy Generator Module

The Strategy Generator module devised strategies for offering tasks of varying challenges through Task Switching Rationale to the participants based on the AS and PS systems.

1) Task Switching Rationale for PS System:: Our VR-based social communication module was designed to have 12 social stories for the PS system which were distributed over four difficulty levels (DLI-IV) with three stories in each level. For PS, tasks of varying challenges were offered based only on one's performance score. One's performance in a particular task was considered as "Adequate," if the score was $\geq 70\%$ of the total score ($140 = 70$ in SIT-I $+ 70$ in SIT-II), otherwise this was considered as "Inadequate." Note that these strategies to classify performance were chosen as a first approximation to quantify social interaction with full recognition that such quantification could be varied in future.

We implemented a dynamic task switching mechanism with finite state machine representation [Fig. 5 (a)]. For "Adequate" task performance (Case "C1") [Fig. 5(a), Table II], task progression continued stepwise while increasing task difficulty. But, for 'Inadequate' task performance (Case "C2"), the system lowered the task difficulty. This continued until tasks in a particular difficulty level were exhausted. Each task

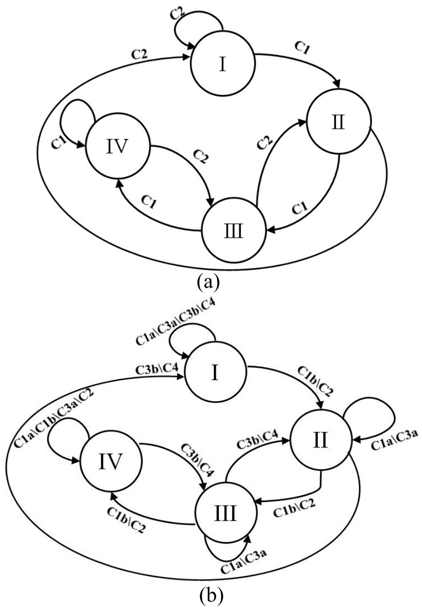


Fig. 5. Task Switching Rationale for (a) PS system (b) AS system Note: C represents Case e.g., C1 refers to Case 1: Refer Tables II and III for more details.

TABLE II
TASK SWITCHING RATIONALE AND FEEDBACK FOR PS

Performance	Action Taken	Case	System Response
Adequate	↑	C1	"You are doing great."
Inadequate	↓	C2	"You can do better."

ended with audio-visual feedback [Table II] to encourage the participant for next task.

2) Task Switching Rationale for AS System: Like the PS system, our AS system also comprised of 12 social stories distributed over four difficulty levels (DLI-IV) with three stories in each level. However, in contrast to PS, for the AS system, the tasks of varying difficulty were presented based on the composite effect of one's predicted anxiety level and the task performance score.

Thus, our AS system fused the information on one's anxiety ("High"/"Low") as predicted by IAP module (Section II-C) and task performance ("Adequate"/"Inadequate") using the concepts of 1) Boredom/Apathy, 2) Flow, 3) Anxious, and 4) Panic state from "flow theory" [33] to dynamically switch tasks of varying difficulty by implementing an individualized task switching rationale [Fig. 5(b), Table III]. There were two cases where the rule design was easier (cases "C2" and "C4"). When the participant performed "Adequately" and had "Low" anxiety [C2 (Table III)], we assumed this condition to be the "Flow state" of the participant. Thus, our AS system offered him a task belonging to a higher difficulty level. When the participant performed "Inadequately" and also had "High" anxiety [C4 (Table III)], we assumed the participant to be in the "panic state," thereby our AS system offered him a task of lower level of difficulty with the hope of having a reduction in his anxiety level and moving towards the "flow state." However, if the participant had "Inadequate" performance and "Low" anxiety

TABLE III
TASK SWITCHING RATIONALE AND FEEDBACK FOR AS SYSTEM

Performance	Predicted Anxiety Level	Action Taken	Case	System Response
Inadequate	Low	→/↑	C1a\C1b	"You can do better. You might find the next story interesting."
Adequate	Low	↑	C2	"You are doing great. You might find the next story also interesting."
Adequate	High	→/↓	C3a\C3b	"You are doing great. Please go ahead with the next story."
Inadequate	High	↓	C4	"You can do better. Please go ahead with the next story."

[C1a (Table III)], we assumed that the participant was in the "boredom /apathy" state and he was not attending to the task. Also, since the anxiety was "Low," we assumed that the task was not difficult for him. To confirm our assumption, we offered him another chance in the same level without taking an immediate decision on task difficulty. If the situation prevailed [C1b (Table III)] then we offered him a task of higher difficulty with the hope of moving him to the "flow state." In contrast, if the participant had "Adequate" performance and "High" anxiety [C3a (Table III)], we assumed that the participant was in the "panic" state. Also, since the anxiety was "High," we assumed that the task was difficult for him. To confirm our assumption, we offered him another chance in the same level. If the situation prevailed [C3b (Table III)] then we offered him a task of lower difficulty with the hope of moving him to the "flow state." Additionally, at the end of each task our AS system provided audio-visual feedback to the participant (Table III).

Both AS and PS systems employed menu-driven conversation interface having multiple-choice options that served as ready reference for the participants facilitating them by offering possible choice options. On the other hand, such an interface might seem not to completely eliminate the possibility of guesswork (or chance) done by the participants while making their response choices. In fact, in contrast to the PS system, we believe that our AS system was capable of eliminating such a possibility by making the Task Switching Rationale sensitive to the composite effect of anxiety and performance, instead of considering only the performance (as in PS). Specifically, in certain situations, such as, cases C1a/1b and C3a/3b (Table III), our AS system recognized these as conflicting situations and thereby did not take an immediate decision to change the task challenge level based on the participant's response. Instead, it considered a sequence of task responses before taking a decision to change the challenge level.

III. EXPERIMENT AND METHODS

A. Participants

For our present study, nine adolescents with ASD were recruited from various nearby special needs schools. All the participants had DSM IV diagnosis with qualitative measures. All the participants (except P6) were screened on core ASD-related symptoms based on measures such as, Social

TABLE IV
PARTICIPANT CHARACTERISTICS

	Age (yrs)	Order of exposure	SCQ	SRS	SCAS
P1(M)	10	PS-AS (G1)	22	75	56
P2(F)	16	PS-AS (G1)	9	59	52
P3(M)	11	AS-PS (G2)	12	61	58
P4(M)	16	AS-PS (G2)	18	65	57
P5(F)	12	PS-AS (G1)	13	60	40
P6(M)	12	AS-PS (G2)	-	-	-
P7(M)	15	PS-AS (G1)	10	58	61
P8(F)	19	AS-PS (G2)	18	75	55
P9(M)	14	AS-PS (G2)	17	72	60

Note: M: Male; F: Female: G1: Group1, G2: Group2

Responsiveness Scale (SRS [34]) with cutoff T-score $\geq$ 60T; and Social Communication Questionnaire (SCQ [35]) with cutoff score of 15. The SRS and SCQ scores indicate that the participants were either within or marginally in the clinical range. Also, Spence Children's Anxiety Scale (SCAS) [36] was used to get an idea of the participants' anxiety level before starting the study. These measures were obtained from their caregiver's feedback, and not from the participant, since research shows that self-report of children with autism is less reliable [37]. For P6, we had the Childhood Autism Rating Scale 2$^{\text{nd}}$ Edition-High Functioning (CARS 2-HF) [38] measure that reported him to be in the Mild to Moderate autism range. We did not have access to Autism Diagnostic Observation Scheduled (ADOS) and IQ scores. However, all the ASD participants were enrolled in special needs schools and their teachers selected them based on their impression of their IQ being above average. Regarding verbal proficiency, the selected participants were conversant in English. The participants were divided into two groups, namely, group 1 (G1) and group 2 (G2). In G1, the participants were exposed to tasks in PS-followed by-AS (i.e., PS-AS) while in G2 they were exposed in reverse order (i.e., AS-PS) (Table IV) for considering the ordering effects.

B. Experimental Setup and Procedure

Our study required commitment of approximately 2 h from each participant, during which they interacted with both PS and AS systems on two different days. Fig. 6 shows the experimental setup in which the participant was asked to sit in front of a Task Computer executing the VR-based tasks. The experiment began with a brief introduction of the experimental setup comprising of the Task Computer, Biopac MP150 along with the physiological sensors, etc. and the steps to be followed by the participant while interacting with the VR-based tasks using a visual schedule. This was followed by signing of the consent form. Also the participant was told that he was free to quit from the study at any time if he felt uncomfortable while interacting with our system. Physiological sensors were carefully placed on the thumb, middle, index and ring fingers of the participant's non-dominant hand. The experimenter then started the execution of the VR-based tasks. The task began with an instruction screen, presented audio-visually, to inform

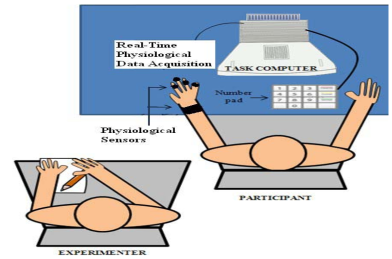


Fig. 6. Experimental setup.

the participant about the task. This was followed by 3 min of baseline recording of physiological signals. The VR-based tasks began with SIT-I sub-task followed by the SIT-II sub-task. While the participant was interacting with our VR-based system, the participant's physiological signals were acquired in a time-synchronized manner.

C. Computation of Normalized Performance Score

In order to quantitatively estimate participants' performance, each of whom could potentially participate in different VR-based social communication tasks (of varying number of trials and difficulty levels), we needed to compute normalized values of the performance scores achieved by the participants (similar to [39]). The formula that we have used to compute the normalized scores is given by equation 1. Here, x_{DLi} represents the average performance score obtained for the task trials in level i, w_{DLi} is the weight assigned to the task in that particular level, and X_{DLi} is the total score (maximum score achievable) in level i task

$$\text{Normalized Performance Score } (\text{Perf}_{\text{NORM}}) = \frac{\sum_{i=I}^{j} x^{*}_{\text{DLi}} w_{\text{DLi}}}{\sum_{i=I}^{j} X^{*}_{\text{DLi}} w_{\text{DLi}}}, \text{ where j is} I/II/III/IV. \tag{1}$$

Since we did not want to penalize the participants, some of whom might not have reached highest level (DLIV) of difficulty and exited without interacting with all the tasks, we considered j as either I/II/III/IV in (1). Let us consider that VR-based task trials of "DLI," "DLII," "DLIII" and "DLIV" had weights (W_{DL}) designated by '1', '2', '3' and '4', respectively. Also, let us assume that one can get an average performance score of 'x_{DLI}', 'x_{DLII}', 'x_{DLIII}', and 'x_{DLIV}', out of maximum possible scores of 'X_{DLI}' 'X_{DLII}', 'X_{DLIII}' and 'X_{DLIV}' (each being 140) for trials of "DLI," "DLII," "DLIII" and "DLIV" respectively. Thus, if a participant interacted with VR-based task trials of "DLI," "DLII," "DLIII" and "DLIV," the normalized performance score($\text{Perf}_{\text{NORM}}$) achieved was

$$\text{Perf}_{\text{NORM}} = \frac{\left(\frac{1}{10}x_{\text{DLI}}\right) + \left(\frac{2}{10}x_{\text{DLII}}\right) + \left(\frac{3}{10}x_{\text{DLIII}}\right) + \left(\frac{4}{10}x_{\text{DLIV}}\right)}{\left(\frac{1}{10}X_{\text{DLI}}\right) + \left(\frac{2}{10}X_{\text{DLII}}\right) + \left(\frac{3}{10}X_{\text{DLIII}}\right) + \left(\frac{4}{10}X_{\text{DLIV}}\right)}. \tag{2}$$

Thus, if one achieved maximum possible scores in tasks of each difficulty level, then his $\text{Perf}_{\text{NORM}}$ was 1.

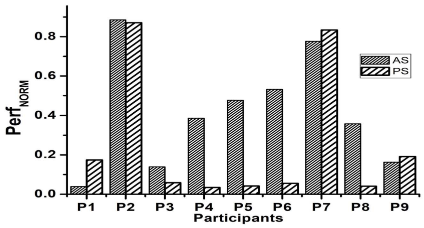


Fig. 7. Variation in $\text{Perf}_{\text{NORM}}$ for all participants.

IV. Results and Discussion

To test whether our PS and AS systems had an impact on the participants' performance and physiology, we designed a usability study, as a proof-of-concept application, in which our participants interacted with VR-based tasks. A post-study survey revealed that the participants liked interacting with the system, did not face any inconvenience with physiological sensors and in understanding the tasks. Thus, this suggests that our system might be accepted by the target population.

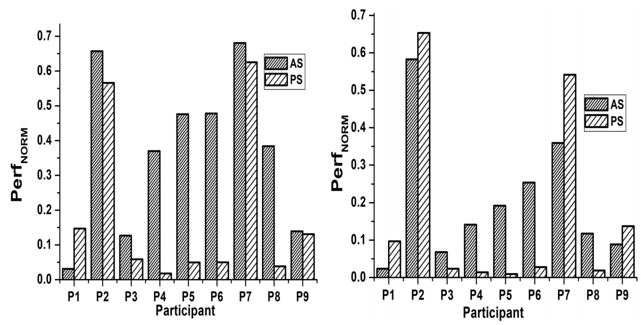
A. Impact of AS and PS Systems on Participants' Overall Performance

While our participants interacted with VR-based tasks, our system computed their performance scores. We calculated the $\text{Perf}_{\text{NORM}}$ for each participant for both AS and PS systems. Results (Fig. 7) suggest that for a majority of participants (6 out of 9), $\text{Perf}_{\text{NORM}}$ improved with a group average improvement of 63.16%, a considerable (marginally statistically significant (p-value= 0.07 using dependent sample t-test) improvement while they used the AS compared to the PS system. On the other hand, the $\text{Perf}_{\text{NORM}}$ while using the PS versus the AS systems were comparable for a few participants ($\%\Delta\text{Perf}_{\text{NORM}} = 6.75\%$ for P2, P7, and P9 on average). The SRS and SCQ scores (Table IV) tell us that P2 and P7 were marginally in the autism spectrum. Based on these findings, we speculate that an AS system with different thresholds for physiological indexes (different from that in Table I) and threshold (different from $\geq$ 70%) for performance score might work better for these participants (however, we are unable to confidently attribute our observation to any specific group of participants because of the small sample size). The experimenter's notes reported that P9 was distracted, looked away from the computer screen and spoke loudly about his previous experiences with movies once the stories on movie theatres were presented to him by the AS system, thereby causing him to miss much of the story content and also not looking at the Avatar_1's face. In contrast to all the other participants, for P1 we see an appreciable reduction in $\text{Perf}_{\text{NORM}}$ from PS to AS (seen from Fig. 7). A possible explanation for this might be that P1 was not attending to the VR-based tasks on the first day (while interacting with PS) while looking around and entering his option choices that might have contributed to making correct choices by chance, as reported by the experimenter.

Additionally an independent sample t-test carried out to test if there were any effects due to the order in which AS and PS based tasks were presented to the two groups of participants, was not statistically significant. This suggests that there were no significant ordering effects due to the order of presentation of VR-based tasks belonging to the PS and AS systems.

TABLE V
Task Trials

	ID	DLI		DLII		DLIII		DLIV	
		AS	PS	AS	PS	AS	PS	AS	PS
Group 1	P1	3	3	0	2	0	0	0	0
	P2	1	1	1	1	1	1	3	3
	P5	2	3	2	0	3	0	1	0
	P7	2	1	1	1	3	2	3	3
Group 2	P3	3	3	2	0	0	0	0	0
	P4	2	3	2	0	2	0	3	0
	P6	2	3	2	0	2	0	3	0
	P8	3	3	2	0	2	0	3	0
	P9	3	3	3	1	0	0	0	0
Total		21	23	15	5	13	3	16	6



(a) (b)

Fig. 8. Variation in $\text{Perf}_{\text{NORM}}$ (a) for SIT-I (b) for SIT-II.

An improvement in one's performance not only depends on the increase in the performance score but also on the number of task trials executed at a higher level of difficulty. Increased number of task trials at higher difficulty suggests that the participant tackled tasks that offered a greater level of challenge. As we can see in Table V, the total number of task trials executed were comparable for AS and PS systems at DL1. However, the picture was different at higher task difficulty levels. The total number of task trials belonging to DLII, DLIII, and DLIV successfully executed by the participants for the AS system was greater than that for the PS system. This suggests that our AS system was able to expose the participants to task trials of increased challenge for a longer duration than the PS system, thereby offering opportunity of improved skill training.

B. Implication of AS and PS Based Systems on Participants' Performance Score During SIT-I and SIT-II Tasks

For each task trial, our VR-based system offered two different sub-tasks, namely SIT-I and SIT-II addressing different aspects of social communication. From Fig. 8(a), we can see that all the participants (except, P1) had an improved performance in SIT-I sub-task in AS system as compared to that in the PS system. P1 was an exception since P1 was not attending to the tasks while interacting with PS (Section IV-A), but rather entering random choices in response to Avatar_2's questions. However, in SIT-II sub-task, we see a different picture for P2, P7, and P9 (along with P1) with the rest of

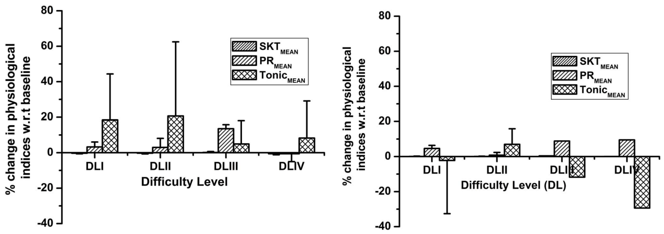


Fig. 9. $\%\Delta Physio_{w.r.tBaseline}$ for AS and PS system for avatar's Happy facial emotional expression.

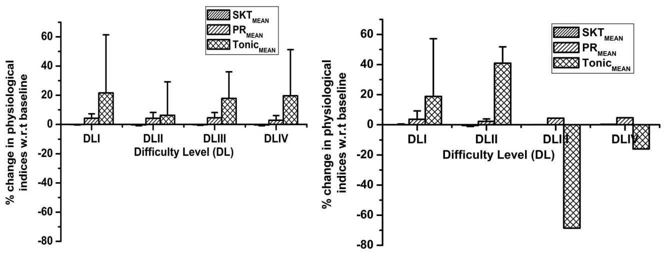


Fig. 10. $\%\Delta Physio_{w.r.t\ Baseline}$ for AS and PS system for avatar's Angry facial emotional expression.

the participants showing improvement in their performance from PS to AS. The reduced performance score of P2, P7, and P9 during AS can be attributed to similar observations as has been mentioned in Section IV-A. Dependent sample t-test on $Perf_{NORM}$ for AS and PS systems showed that the scores for SIT-I sub-tasks were statistically significantly different (p-value$= 0.03$) but not for SIT-II (p-value> 0.05). Fig. 8 (a) and (b) shows the $Perf_{NORM}$ for AS and PS systems during the SIT-I and SIT-II sub-tasks.

C. Implications of Avatars' Emotions on Participants' Physiology for AS and PS Systems

During SIT-II, the $Avatar_1$ narrated her personal experience by demonstrating context-relevant facial emotional expressions. After her narration, the $Avatar_1$ asked emotion-related and personal feeling related questions to the participants for tasks belonging to DLIII and DLIV. While the participants interacted with VR-based tasks, our system acquired their physiological signals. Figs. 9 and 10 show the percentage change in physiological indexes ($\%\Delta Physio_{w.r.t\ Baseline}$) e.g., SKT_{MEAN}, PR_{MEAN} and $Tonic_{MEAN}$ with respect to Baseline corresponding to $Avatar_1$'s happy and angry emotions, respectively, for DLI-IV.

When exposed to $Avatar_1$'s happy emotional expression (Fig. 9), we observe an overall increase in $Tonic_{MEAN}$ and decrease in SKT_{MEAN} from DLI to DLII tasks for both PS and AS systems, possibly implying an increase in the participants' anxiety level. Further, as the participants progressed to tasks belonging to higher levels of difficulty, i.e., DLIII and DLIV, the participants' overall physiological indexes reflected a decrease in their anxiety level while interacting with the AS system. For the PS system, for tasks belonging to DLIII and DLIV, we observe a reduction in the participants' overall physiological indexes ($\%\Delta$ PR_{MEAN} $=$ 7.5% and $\%\Delta$ $Tonic_{MEAN}$ $=$ 150% [Fig. 9 (b)] which might imply reduced anxiety. However, on further analysis we found that only two ASD participants (P2 and P7) who were marginally into the autism spectrum were able to reach VR-based tasks belonging to DLIII and DLIV during the PS system. In contrary, a majority of the participants were able to interact with DLIII and DLIV tasks for the AS system.

Again when exposed to the $Avatar_1$'s angry emotional expression, we see that the variation of physiological indexes with difficulty level for both AS and PS systems, shows similar trend to that when exposed to the happy facial expression. Though we see similar trend, yet, the magnitude of the change in the physiological indexes was found to be more for the angry emotion as compared to that for the happy emotion for both systems. Again, Figs. 9 and 10 show that the variation in physiological indexes with difficulty level was more pronounced for PS system than that for the AS system. In fact, for angry emotion, we find that the $Tonic_{MEAN}$ remained almost constant with a slight increase ($\%\Delta = 9.87\%$) from DLIII to DLIV for AS system [Fig. 10(a)] and a considerable increase (($\%\Delta = 76.7\%$) from DLIII to DLIV for PS system [Fig. 10(b)]. Additionally from Figs. 9 and 10 we observe an increased variability in the % change in physiological indexes for the AS system as compared to the PS system as is evident from the error bars. However, please note that the smaller variability for the PS system can be due to the fact that only few participants were able to move to higher difficulty levels for the PS system as compared to that for the AS system (Table V).

To summarize, with our AS system, a majority of our participants were able to interact with more number of tasks belonging to higher difficulty levels as compared to PS system with varying implications on the predicted anxiety.

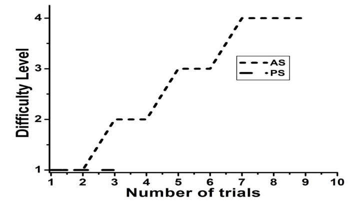


Fig. 11. Task progression for P6.

D. In-Depth Analysis of the Implications of AS and PS Systems for one Participant - a Case Study

Here we present an in-depth case analysis for P6. First we will look at his nature of task progression and performance in the VR-based tasks and then the implications of our VR-based systems on his physiological indexes.

Fig. 11 shows the task progression for P6 for the AS and PS systems. For PS system, P6 interacted with only DLI tasks. On the other hand, for AS system, P6 was able to interact with more number of tasks distributed over DLI-DLIV (Table V) than that for PS. For AS system, the task progression trajectory showed a gradual improvement that cannot be seen for the PS system. Also, P6 was able to achieve higher $Perf_{NORM}$ score during AS system as compared to the PS system (Fig 7 (Section IV-A).

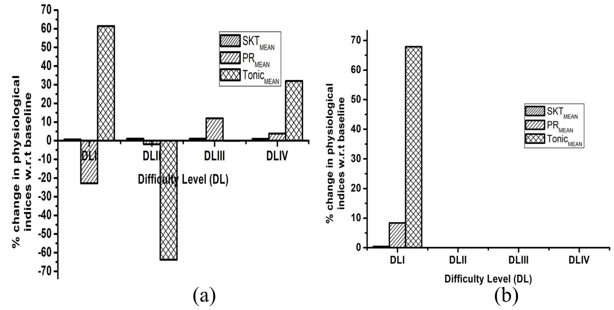


Fig. 12. $\%\Delta\text{Physio}_{\text{w.r.t Baseline}}$ for P6 (a) AS and (b) PS systems.

Both the AS and PS systems also had implications on his $\text{Tonic}_{\text{MEAN}}$, PR_{MEAN} and SKT_{MEAN}. Fig. 12(a) and (b) shows the percent change ($\%\Delta$) in the physiological indexes of P6 with respect to baseline for AS and PS systems, respectively. While interacting with PS system there was an increase in $\text{Tonic}_{\text{MEAN}}$ and PR_{MEAN} for DLI tasks from baseline which might imply an increase in anxiety. Thus a possible explanation of P6 not being able to move to tasks of higher difficulty for the PS system can be due to increase in anxiety as reflected from his physiological indexes. However, for AS system, although we see an increase in $\text{Tonic}_{\text{MEAN}}$ for DLI tasks from baseline which might imply an increase in anxiety, different inferences can be made for tasks of higher difficulty levels. In fact, the $\%\Delta$ in $\text{Tonic}_{\text{MEAN}}$ from baseline for DLII was much lower than that for DLI task, which might indicate a reduction in his anxiety level. Further, for DLIII and DLIV tasks, P6 showed an increase in the $\text{Tonic}_{\text{MEAN}}$ with respect to baseline that was in fact lower than that during DLI task which again can be interpreted as contributing to reduced anxiety for P6. For the other physiological indexes, the variation was much less as compared to $\text{Tonic}_{\text{MEAN}}$. Among all the physiological indexes, the variation in skin temperature with task difficulty was the least for P6.

E. In-Depth Analysis of Implication of SIT-I and SIT-II Sub-Tasks on Physiology and Performance for Both AS and PS Systems: A Case Study

From Fig. 12(a) and (b) it is evident that both PS and AS systems had varying implications on the physiological indexes of P6 as far as DLI tasks were concerned (with no DLII-DLIV tasks for PS system). Further, we were interested to understand the implication of each of SIT-I and SIT-II sub-tasks on P6 as far as physiology was concerned. With this motivation, we went for an in-depth analysis to understand the implication of SIT-I and SIT-II sub-tasks on physiological indexes for both AS and PS systems, particularly for DLI tasks [Fig. 13(a) and (b)]. For both AS and PS systems, we observe that variation of all the physiological parameters reflected increased anxiety in SIT-II compared to that in SIT-I which is expected, since exposure to emotional expressions on the social communicator's face (during SIT-II) is often anxiety-provoking in individuals with ASD. In addition, we also find that the $\%\Delta$ in $\text{Tonic}_{\text{MEAN}}$ with respect to Baseline for SIT-II in AS system was much less as compared to that for SIT-II in PS system. This might imply that P6 was less anxious while interacting with the AS system. Similar inference can also be drawn for SIT-I sub-task with the AS system being less anxiety-provoking than the PS system as can be seen from $\%\Delta$ in $\text{Tonic}_{\text{MEAN}}$ with respect to Baseline (the $\%\Delta$ in other indexes with respect to Baseline being smaller).

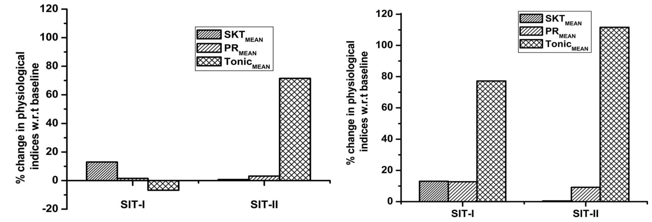


Fig. 13. $\%\Delta\text{Physio}_{\text{w.r.t Baseline}}$ for SIT-I and SIT-II subtasks (a) For AS (b) for PS.

In fact, the anxiety of P6 while interacting with SIT-I and SIT-II sub-tasks had implications on his performance as well. Fig. 8 shows the normalized weighted performance score ($\text{Perf}_{\text{NORM}}$) of all participants for SIT-I and SIT-II sub-tasks belonging to both AS and PS systems. From Fig. 8, we observe that the $\text{Perf}_{\text{NORM}}$ score of P6 for SIT-I was more than that for SIT-II (for both AS and PS systems), with the $\text{Perf}_{\text{NORM}}$ for AS being higher than that for PS. Since, SIT-II was more challenging than the SIT-I, SIT-II might have led to increased anxiety (as evident from physiological indexes) thereby resulting in reduced performance score for P6 than that during SIT-I. Again, the performance for SIT-II sub-task of PS was lower than that for SIT-II of the AS system. This might be due to the fact that P6 was less anxious while interacting with AS system compared to that with PS system, which is also evident from the reduced $\%\Delta$ in $\text{Tonic}_{\text{MEAN}}$ with respect to Baseline [Fig. 13(a) and (b)].

In summary, we can say that though P6 was found to be more anxious during SIT-II than during SIT-I (for both AS and PS systems), yet, the level of anxiety for SIT-II belonging to AS system was less as compared to that belonging to the PS system.

V. Conclusion

In the present work, we have developed a VR-based Anxiety-sensitive (AS) system that can adapt itself to the composite effect of one's performance and anxiety level mapped from physiology-related biomarkers. In this paper, we have presented the system design and results of a preliminary usability study developed as a proof-of-concept application. Prior to testing for statistical significance we tested the data for normal distribution using Shapiro-Wilk test for normality. From this test we assured that mostly the data was normally distributed. Preliminary results of the usability study with the limited sample size indicate the potential of our VR-based system to cause variations in one's performance measure along with improvement in task progression pattern while interacting with AS system as compared to the Performance-sensitive (PS) system. Thus, this study paves the way towards using an intelligent adaptive system that holds promise for its applicability in designing intervention paradigms aimed at improving social communication skills for children with autism.

In the present study, we have incorporated both physiology and performance data of the participants in the design of the AS system and its rendering might seem to result in less naturalistic social interaction. However, the prediction of anxiety from physiological indexes was carried out by AS system in the backend and the participant was not aware of the data processing that was being done by our system. Again, providing sensors on the participant's hand for acquisition of physiological signals might seem to take away the naturalistic feel of social communication. However, these sensors being light-weight and stick-on type had not been reported by the participants as inconvenient. With advancement in computing technology and electronics, such a set-up can be easily made available at one's home, school or therapist's clinic thereby serving as a complementary tool in the hands of the therapist.

There are certain limitations of the current study that warrant consideration. In this study, we have used a menu-driven conversational interface with mouse and keypad as input devices, instead of using a more realistic and active communication mode such as, verbal or text-chat-based interface. We chose the less active model of menu-driven conversation, since we wanted to control the complexity of the interaction environment that might impose an additional degree of anxiety in the participants. Thus, we wanted to keep our skill learning platform as a controlled one that is important particularly during initial skill training. Once we find our participants feeling comfortable in interacting with our current VR-based system, we plan to gradually incorporate flexibility in the communication process in future by incorporating verbal communication through speech recognizer modules with built-in Natural Language Processing facility for more realistic bidirectional conversation.

Again, one of the major limitations of our current study before its application to an intervention paradigm is that our system needs to be verified by a larger participant pool. In the present research, our aim was to design VR-based system as a proof-of-concept application and see its efficacy with a limited sample size. However, a much larger study of the current system would be needed to understand how our current findings impact areas of core deficit for individuals with ASD and how such impact can be generalized to the heterogeneous population of individuals with the disorder.

Yet other limitation is that in our study we did not use eye-tracking to understand the specific stimuli to which the participant was paying attention. Since, the tone of the avatar's voice was maintained as flat, we assumed that if one needs to decipher the emotion from the facial expression of the virtual social communicator, then the participant had to look towards the face of the communicator. Thus, in our present study we did not use any eye-tracker to have quantitative measure of whether a participant was really looking towards the face of the virtual social communicator during the VR-based task. In future, we plan to augment our existing system with eye tracking facility so as to make our task switching rationale more robust while incorporating both the peripheral and gaze-related physiological indexes and one's looking pattern along with performance.

Another limitation of our present study is the use of costly physiological data acquisition device, e.g., Biopac MP150 to acquire one's physiological indexes that can be mapped to anxiety level. The Biopac MP150, a standard device is capable of making real-time acquisition of a large number of physiological signals. In our study, we needed to acquire only three physiological signals with Biopac MP150 to predict one's anxiety. It is true that the use of costly Biopac MP150 would restrict the applicability of our physiology-based anxiety prediction mechanism for the general population. Actually, the standard device, Biopac MP150 was used in our study as an initial step to work with one's physiological signals that were acquired with a satisfactory level of accuracy and thereby confirm the feasibility of an anxiety-sensitive system to be used as a social communication skill learning platform for children with autism. Once the feasibility of anxiety being predicted from physiology-related biomarkers is proved, in future we intend to replace the Biopac MP150 by low-cost physiological data acquisition device with the data being benchmarked with Biopac MP150, thus making our system low-cost and accessible to the general population in autism.

The current study shows that our intelligent adaptive VR-based anxiety-sensitive system has a potential to provide training to improve some of the core social communication skills of individuals with ASD within the simulated training environment. However, questions on the transferability of the learned social communication skills from the simulated VR-based environment to real-world situations remain to be addressed in future. We hope that such an individualized VR-based platform can be a potent complementary tool in the hands of the interventionist so as to contribute to our endeavors in improving functioning and quality of life for individuals with ASD.

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