The Effect of Automation and Workspace Design on Humans' Ability to Recognize Patterns While Fusing Information

Kellie L. Turner

Michael E. Miller

Air Force Institute of Technology
AFIT/ENV
Wright-Patterson AFB, OH 45433

***Abstract*—Increasingly complex contested environments force analysts to combine many different types of intelligence data to form a more cohesive picture of the environment. Information fusion systems include computers that integrate and synthesize information from multiple sources and humans who combine that information with reasoning abilities and knowledge of past events to assess situations and predict future states. The intent of this paper is to highlight the importance of understanding human cognition and decision making by presenting the hypotheses of our current research. The purpose of the future study described in this paper is to investigate how the degree of information acquisition automation used affects the human's ability to detect patterns in data that may be needed to reach higher levels of information fusion. This study will use a 2 (task type: intuitive, analytic) x 3 (amount of automation: none, half, all), between subjects experimental design. We expect to find a significant interaction between task type and amount of automation. For tasks that induce the human's intuitive system, increasing automation is expected to disrupt the human's ability to recognize patterns. However, for tasks that induce the human's analytic system, increasing automation is expected to improve the human's ability to discern patterns. The results of this research can inform guidelines for the design of common workspaces to support human-machine teaming in future information fusion systems.**

Keywords—information fusion; automation; human-machine team; analytic processes; intuitive processes

I. INTRODUCTION

With increasingly complex contested environments, analysts must now integrate diverse intelligence data to build a cohesive picture of the environment. Today's sensor technology, with the ability to collect vast amounts of data at a rapid pace, should enable intelligence analysts to make more sense of the world than ever before. However, this access to increasing amounts of data comes at a cost. Very large volumes of highly heterogeneous, complex data have long been shown to hinder analysts' sense-making process [1]. Machine fusion systems are critical for simplifying complex data, identifying the most relevant data, and displaying data in a way that aids analyst interpretation and decision making.

Information fusion is a process of integrating and synthesizing information derived from multiple sources [2]. High-level fusion requires an awareness of complex relations between past and future events as well as present knowledge and expertise, making humans' roles significant and crucial to the success of this process [3]. Because the human is essential to the process, information fusion systems can be viewed and understood as human-machine teams. Adding automation has been found to have both positive and negative outcomes on task performance. Automating parts of a task can free up resources to allow the human to better perform other tasks. However, automation has been blamed for task degradation and poor situation awareness in the event of automation failure [4, 5]. A solid understanding of human cognition allows information fusion workspaces to be designed in a way that will enhance the human's ability to recognize patterns in the information.

The intent of this paper is to highlight the importance of understanding human cognition and decision making by presenting the hypotheses of our current research on how automation can influence the ability of people to recognize patterns. We begin with a brief summary of information fusion, human-machine teaming, and human cognition research to identify a research gap that could impede the development of effective common workspaces in information fusion systems. We then present an experimental design for investigating the differential effects of automating information acquisition on intuitive verses analytic processing. We will reiterate the expected results and discuss the significance of this research for the design of information fusion systems.

The Data Fusion Information Group (DFIG) model [6], an extension the earlier Joint Directors of Laboratories (JDL) data fusion model [7], distinguishes between different levels of fusion based on the goals of the fusion process. Low level fusion (Levels 0 and 1) concerns numerical data and is performed by machines. Level 0, Data Assessment, uses pixel or signal level data association and characterization to hypothesize the presence of a signal and estimate and predict its observable states. Level 1 fusion (Object Assessment) combines data on target objects for identification. Levels 2 and 3, considered high-level fusion, are typically performed by humans. Level 2, Situation Assessment, aggregates the target information with the goal of identifying meaningful events and activities to increase understanding. Level 3 fusion goes a step further by assessing impacts relative to mission objectives, and includes goals such as estimating threat levels, predicting decision outcomes, and determining vulnerabilities and possible courses of action [8, 9]. The current research focuses on levels 0-3 of the information fusion process as it is at these levels where pattern recognition is most important (see [10] for a discussion of higher levels of information fusion).

Humans and machines bring different strengths to the information fusion process. Machines are more efficient at combining structured, hard (machine-derived) data. Humans are currently better than machines at combining soft (human-derived) data as it is usually unstructured [11] and uncertainty levels are unknown [12, 13]. One human role is frequently to support automated computer reasoning techniques with visual and aural pattern recognition and semantic reasoning [14]. However, as previously acknowledged within the information fusion literature [15, 16], there is little emphasis on how to present information to aid the human's ability to recognize patterns and reason about the information. Viewing an information fusion system as a human-machine team with shared goals should encourage system designers to consider human factors aspects. Humans and machines must work collaboratively and respond in a situation-adaptive manner for true human-machine co-agency to exist [17]. In many domains, this harmony cannot be realized because, ultimately, a machine does not have values and cannot be held accountable for decisions resulting in disaster [18]. However, the information fusion domain is ripe for the application of human-machine teaming research as the human and the machine have complementary strengths, that when combined, can enhance the fusion process.

Reference [19] proposed a four-stage view of human information processing that includes information acquisition, information analysis, decision and action selection, and action implementation to correspond to the equivalent system (or machine) stages. In this framework, any of the four stages may be automated at a level of 1-10, with 1 being completely manual and 10 being completely automated. Higher levels and later processing stages generally require increasing degrees of automation as it is typically assumed that later stage automaton includes at least the level of automation in the earlier stages. Reference [20] conducted a meta-analysis of 18 automation studies and concluded that there is a critical difference in the benefit of automation for tasks supporting information analysis verses tasks supporting action selection. Automation supporting information analysis enhanced performance, while automation supporting action selection had negative consequences. However, many studies on automation using the model found in [19] have conflicting results. For example, [21] found that information automation (both acquisition and analysis) hurts expertise development whereas decision automation accelerates expertise development. Patterson [22] suggested that many of the conflicting results from these studies may be due to the fact that the original levels of automation in the model found in [19] focused solely on analytical processing and neglected intuitive cognition.

How do people integrate information? One might imagine that people consciously search for information and reason about how it is put together and what it might mean. They might also search through their memories for similar problems that they have encountered before to try to make sense of the current situation. This process would be deliberate and effortful. However, early evidence within the research literature on Gestalt psychology points towards a more unconscious process, one in which people have trouble explaining how or why they assemble cues to perceive the whole because it occurs outside of their awareness. A gestalt is an integrated coherent structure or form, a whole that is different from the sum of its parts. Gestalts emerge spontaneously from self-organizational processes in the brain. An emergent feature is perceived when parts combine into wholes; it is a feature possessed by wholes, but not any individual part nor any single group of parts [23, 24]. Early psychologists demonstrated that these perceptual processes also apply to cognition [e.g., 25].

Following from Gestalt psychology, information is combined into a complete idea or solution spontaneously by reorganizing the information within the brain. Research shows that humans use two different cognitive systems to reason about the world [e.g., 26-29]. Dual Process theories account for two different systems of thinking, one that is based upon unconscious pattern recognition, and the other based upon more deliberate conscious processing that requires working memory resources. Type 1 processes, also known as intuitive processes, are those that do not require working memory and operate autonomously. They tend to be quick, have high capacity, and operate outside of conscious awareness. This type of processing, based on past experience, is contextualized and operates by subconscious pattern recognition formed from statistical regularities encountered in the environment. Type 2 processing, also known as analytic processing, involves cognitive decoupling (the ability to distinguish supposition from belief) and hypothetical thinking. Analytic processing puts a strong load on working memory. These processes are typically conscious, slow, capacity-limited, and processed serially. As such, analytic processing is correlated with cognitive ability [30].

Results from these three different fields of research reveal something important about how humans and machines integrate information and how the common workspace between them affects a human's ability to detect patterns in data. According to the information fusion literature, analysts must recognize patterns in the data to reach levels 2 and 3 of information fusion, but this specific literature lacks any research on how humans actually perform pattern recognition. Human cognition research contains neurological evidence suggesting that pattern analysis is a distinct skill that does not require specific conscious processing [e.g., 31]. This research also contains prolific experimental evidence that people can and do integrate vast amounts of information outside of conscious awareness [25, 32, 33]. These results suggest that a common workspace between the human and the machine in an information fusion system should foster pattern recognition so long as it induces the human's intuitive system. From the human-machine teaming research, [21] presumed that his discovery that expertise development was hindered by automating information acquisition occurred because automating the acquisition process hinders a learner's ability to reason about an activity. Other studies produced mixed results regarding the effects of automating information acquisition.

However, the air traffic control task in [21] was a very perceptual task and ripe for inducing intuitive cognition. Because the intuitive system is not workload dependent, increasing automation should not significantly benefit performance on an intuition-inducing task. In fact, it is possible that for this type of task, automating information acquisition could cause people to miss patterns formed by the information in the environment that they would have recognized if they were acquiring the information on their own. However, for tasks that engage the analytic system, decreasing workload by automating information acquisition should improve the human's ability to learn patterns because the analytic system relies on working memory, which is limited in capacity. The combination of results from these three distinct research communities led to the rationale for the current research.

II. Current Research

This research will investigate how automating part of the information fusion process affects humans' pattern recognition abilities. The purpose of the study is to investigate how the amount of automation of information acquisition used to support human sensory processes affects the human's ability to detect patterns in data needed to reach higher levels of information fusion. Specific objectives are: 1) To determine how human-machine teaming facilitates the human's ability to learn patterns, and 2) To determine, based on task-type (intuition-inducing vs analytic-inducing), how the common workspace between a human and machine should be structured to aid the human's ability to recognize patterns.

A. Hypotheses and Experimental Design

This study will use a 2 (task type: intuitive, analytic) x 3 (amount of automation: none, half, all), between subjects experimental design, with 8 participants in each condition. Participants will consist of graduate students recruited from a local university. The dependent measure will be performance on forced-choice test trials, in which success requires one to learn patterns during training trials.

- Hypothesis 1: For fully manual tasks, humans will perform better at pattern recognition using a workspace that favors the intuitive system than using a workspace that favors the analytic system.
- Hypothesis 2: As the amount of information acquisition automation increases for intuitive tasks, the human's pattern recognition performance will decrease.
- Hypothesis 3: As the amount of information acquisition automation increases for analytic tasks, the human's pattern recognition performance will increase.

B. Method

a) Materials. Intuitive processes are thought to emerge through implicit learning, which occurs when people learn without intention or, sometimes, awareness. Through implicit learning, people encode tacit knowledge based on statistical regularities encountered in the environment, enabling intuitive decision making and expertise development [34]. One methodology used for implicit learning studies is to use a finite-state grammar as a way of generating complex yet seemingly random patterns [e.g., 35, 36]. Different paths through the grammar produce different sequences of objects. The current study will use a finite-state grammar to generate the stimuli patterns.

For this task, people will be asked to use information obtained from a text chat window to record the daily route traveled by a person of interest. The possible routes of the person of interest will be generated using a finite state grammar, with each path through the grammar representing one route of that person for one day. Information will be defined as the route traveled in one day, which corresponds to the information acquisition processing stage and to Level 1 fusion (object identification, with the "object" being the route). Information Analysis will be defined as the pattern built from experiencing multiple routes, which also corresponds to Level 2 fusion (gaining a better understanding of the situation). Level 3 Fusion will be measured during test trials. Like the training trials, information will be obtained through a chat window. Half of the routes will be unexperienced paths taken through the same finite-state grammar as used during training, and half of the routes will violate the rules of the finite-state grammar, but will use the same possible stops. The participant's task will be to determine if the person violated his or her normal pattern of activity, indicating that he or she is about to perform a violent act (projection in the future for impact assessment), also corresponding to [19]'s decision making processing stage.

The two independent variables will be task type and amount of automation. Task type will be manipulated by the workspace to either favor intuitive processing or analytic processing. Intuitive processes are more likely to engage with perceptual cues, whereas analytic processes operate more on symbolic cues [37]. The procedure for the intuition-inducing task will involve plotting points and drawing routes of a person of interest on a map, which is a very perceptual workspace. For the analytic-inducing task, the participant will obtain the information from a chat window, look at the same map used in the intuition-inducing task, and type the name of the locations in order, essentially creating a list of waypoints. The workspace is no longer the map, but a document on which to type. This task involves words, making it symbolic in nature. Additionally, looking at the map to obtain the name of the location of the stop before typing it into another workspace generates additional workload than that for the intuitive task. This type of workspace is more likely to induce the analytic system. The amount of automation will be manipulated to study how it affects pattern recognition. In the fully manual task, the human will obtain coordinates from a chat window and record the routes between the points. In the human-machine teaming condition, the computer will record half of the routes and the human will record half of the routes. In the fully automated condition, the human will watch the machine record the routes between coordinates.

b) Procedure. Participants will be randomly assigned to one of six conditions. After receiving instructions, participants will begin the training session. They will not be informed that there is a pattern or that there will be a test. The length of the training session will depend on the complexity of the grammar used (to be determined in pilot tests). After the training session, participants will perform the test. The test will resemble the training, except after each route the subject will have to answer whether the person violated his normal pattern of activity. They will not receive feedback on accuracy. The experiment is expected to take one hour or less.

III. Expected Results

Recognition accuracy will be measured and compared across the groups. A significant interaction between task type and amount of automation is anticipated. For tasks that induce the human's intuitive system, increasing automation is expected to disrupt the human's ability to recognize patterns in data. However, for tasks that induce the human's analytic system, increasing automation is expected to improve the human's ability to recognize patterns in data.

IV. Discussion

The principle results of this planned research can feed into the design of common workspaces to support human-machine teaming in future information fusion systems. Fig. 1 depicts how a human-machine team could operate within an information fusion system. Data is collected from the environment, potentially from a variety of different sources, to include sensors, internet, other computers, written reports, etc. The data is then allocated to either a human or a machine, depending on what the machine can or cannot handle or what processing needs can be performed upon the data. The machine performs low-level fusion while the human employs reasoning and uses information stored in long-term memory to perform high-level fusion. There is a common workspace where both the human and machine can deposit and use information after processing, with the higher-level goal of accurately reaching Levels 2 and 3 Fusion. In human teams, a common view of the workspace enhances task performance by providing feedback about the state of the joint task and facilitating communication [38], both of which foster common understanding between the teammates. The common workspace can help with creating a shared perception and common understanding of the information between a human and machine.

If our hypotheses are supported, implications abound for how to design information fusion systems. If possible, humans' workspaces should be designed to aid their ability to recognize patterns in data, meaning the workspaces should induce their intuitive systems. If automating information acquisition hurts this pattern-recognition ability, then information fusion systems should focus more on automating data analysis or decision selection rather than information acquisition. For cases in which this is not possible, computers should allow humans to participate in information acquisition by retrieving and highlighting information to humans, allowing humans to place the information in the workspace. If it is impossible to design the workspace to trigger humans' intuitive systems, the more information computers can add to common workspaces, the more humans' working memory resources will be freed, facilitating the use of their analytic systems to perform conscious pattern recognition.

V. Conclusion

In a human-machine team, the human's ability to use intuition instead of rational thought, which a computer cannot do, brings a team strength that should not be forgotten in the drive to automate more and more tasks. Understanding how automation affects the human's intuitive processes is a critical step in the design of effective information fusion systems. Based on our review of previous research and what we know about human cognition and automation, if our results support our hypotheses, we will demonstrate that automating information acquisition for tasks that drive the intuitive system will be deleterious for humans' ability to recognize patterns in data, and ultimately harm high-level information fusion. However, for tasks that drive the human's analytic system, automating information acquisition will greatly enhance the human's ability to recognize patterns in data. These results will be significant when designing the common workspace between humans and machines in information fusion systems.

VI. Disclaimer

The views expressed in this paper are those of the authors and do not reflect the official policy or position of the United States Air Force, the Department of Defense, or the U.S. Government.

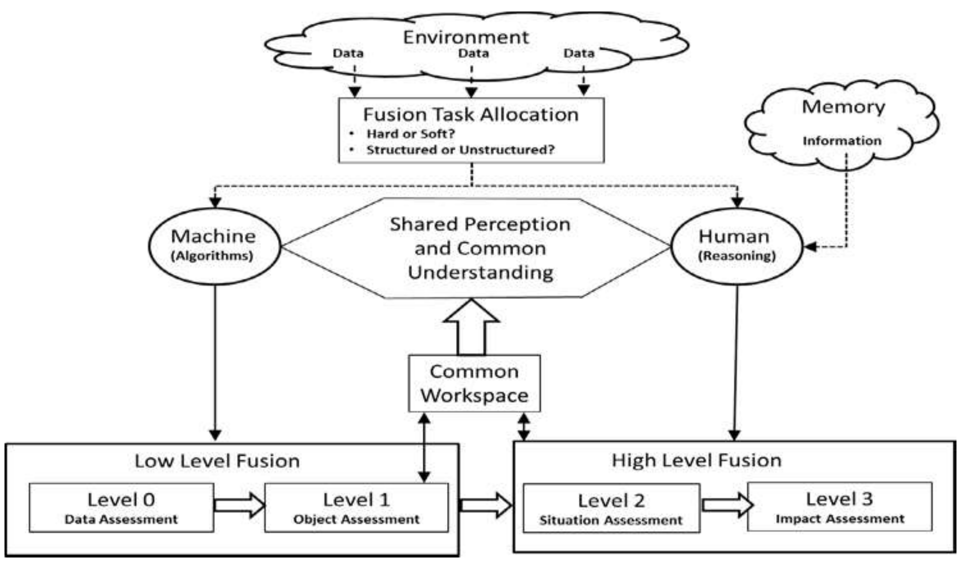

Fig 1. Human-Machine Teaming for an Information Fusion System

REFERENCES

[1] W.C. Elm, M.J. Cook, F.L. Greitzer, R.R. Hoffman, B. Moon, and S.G. Hutchins, “Designing support for intelligence analysts,” in Proc. of the Human Factors and Ergonomics Soc., vol. 48, no. 3, pp. 406-410, 2004.

[2] B. Khaleghi, A. Khamis, F. Karray, and S. Razavi, “Multisensor data fusion: A review of the state-of-the-art,” Info. Fusion, vol. 14, 2013, pp. 28-44.

[3] E.P. Blasch, D.A. Lambert, P. Valin, M.M. Kokar, J. Llinas, S. Das, C. Chong, and E. Shahbazian, “High level information fusion (HLIF): Survey of models, issues, and grand challenges,” IEEE A&E Systems Magazine, 2012, pp. 4-20.

[4] P.A. Hancock, R.J. Jagacinski, R. Parasuraman, C.D. Wickens, G.F. Wilson, and D.B. Kaber, “Human-automation research: Past, present, and future,” Ergonomics in Design, vol. 21, no. 9, pp. 9-14, 2013.

[5] A. Sethumadhavan, “Effects of automation on air traffic controller situation awareness and performance,” in Proc. of the Human Factors and Ergonomics Soc., pp. 1-5, 2009.

[6] E. Blasch, I. Kadar, J. Salerno, M.M. Kokar, S. Das, G.M. Powell, D.D. Corkill, and E.H. Ruspini, “Issues and challenges in situation assessment (Level 2 fusion),” J. of Advances in Info. Fusion, vol. 2, pp. 122-139, 2006.

[7] F.E. White, “A model for data fusion,” in Proc of the First National Symposium on Sensor Fusion, 1998.

[8] E. Waltz, “Data Fusion in offensive and defensive information operations,” NSSDF Symposium, 2000.

[9] M.M Kokar and G.W. Ng, “Guest Editorial: High-level information fusion and situation awareness,” Info. Fusion, vol. 10, pp. 2-5, 2009.

[10] E. Blasch, A. Steinberg, S. Das, J. Llinas, C. Chong, O. Kessler, E. Waltz, and F. White, "Revisiting the JDL Model for Information Exploitation," in 16th Int. Conf. on Info. Fusion, Istanbul, Turkey, 2013.

[11] M.A. Pravia, R.K. Prasanth, P.O. Arambel, C. Sidner, and C. Chong, “Generation of a fundamental data set for hard/soft information fusion,” In Proc. of the 11th Int. Conf. on Info. Fusion, Cologne, Germany: IEEE, 2008.

[12] M.P. Jenkins, G.A. Gross, A.M. Bisantz, and R. Nagi, “Towards context aware data fusion: Modeling and integration of situationally qualified human observations to manage uncertainty in a hard + soft fusion process,” Info. Fusion, vol. 21, pp. 130-144, 2015.

[13] D.L. Hall, M. McNeese, J. Llinas, and T. Mullen, “A framework for dynamic hard/soft fusion,” In Proc. of the 11th Int. Conf. on Info. Fusion, Cologne, Germany: IEEE, 2008.

[14] D.L. Hall, M.D. McNeese, D.B. Hellar, B.J. Panulla, and W. Shumaker, “A cyber infrastructure for evaluating the performance of human centered fusion,” In Proc. of the 12th Int. Conf. on Info. Fusion, IEEE, pp. 1257-1264, 2009

[15] M. Riveiro, “Evaluation of uncertainty visualization techniques for information fusion”, in 10th Int. Conf. on Info. Fusion, 2007

[16] M.J. Hall, S.A. Hall, and T. Tate, “Removing the HCI bottleneck: How the human-computer interface (HCI) affects the performance of data fusion systems”, in Hanbook of Multisansor Data Fusion, D. Hall and J. Llinas, Eds. CRC Press, 2001, pp. 19-1 – 19-11.

[17] T. Inagaki, “Human-machine coagency for collaborative control”, in Cybernetics: Fusion of Human, Machine and Information Systems, Y. Sankai, K. Suzuki, and Y. Hasegawa, Eds. Japan: Springer, 2014, pp. 235-265.

[18] P. Stensson and A. Jansson, “Autonomous technology – sources of confusion: A model for explanation and prediction of conceptual shifts”, Ergonomics, vol. 57, no. 3, pp. 455-470, 2014.

[19] R. Parasuraman and T.B. Sheridan, “A model for types and levels of human interaction with automation,” IEEE Transactions on Systems, Man, and Cybernetics – Part A: Systems and Humans, vol. 30, no. 3, pp. 286-297, 2000.

[20] L. Onnasch, C.D. Wickens, H. Li, and D. Manzey, “Human performance consequences of stages and levels of automation: An integrated meta-analysis,” Human Factors, vol. 56, no. 3, pp. 476-488, 2013.

[21] M. Jipp, “Expertise development with different types of automation: A function of different cognitive abilities,” Human Factors, vol. 58, no. 1, pp. 92-106, 2016.

[22] R.E. Patterson, “Intuitive cognition and models of human-automation interaction,” Human Factors Special Section: Cog. Science and Neuroergonomics: Their Dimensions, Their Impact, and the Future of Human Factors/Ergonomics, in press.

[23] J. Wagemans, J. Feldman, S. Gepshtein, R. Kimchi, J.R. Pomerantz, P.A. van der Helm, and C. van Leeuwen, “A century of gestalt psychology in visual perception: II. Conceptual and theoretical foundations,” Psych. Bulletin, vol. 138, no. 6, pp. 1218-1252, 2012.

[24] J. Wagemans, J.H. Elder, M. Kubovy,S.E. Palmer, M.A. Peterson, M. Singh, and R. von der Heydt, “A century of Gestalt psychology in visual perception: I. Perceptual grouping and figure-ground organization,” Psych. Bulletin, vol. 138, no. 6, pp. 1172-1217, 2012.

[25] N.R.F. Maier, “Reasoning in humans: II. The solution of a problem and its appearance in consciousness,” J. of Comparative Psych., vol. 12, no. 2, pp. 181-194, 1931.

[26] J.S.B.T. Evans, “Heuristic and analytic processes in reasoning,” British J. of Psych., vol. 75, pp. 451-468, 1984.

[27] R. Patterson, B. Pierce, H.H. Bell, D. Andrews, and M. Winterbottom, “ Training robust decision making in immersive environments,” J. of Cog. Engineering and Decision Making, vol. 3, no. 4, pp. 331-361, 2009.

[28] V.F. Reyna, “A new intuitionism: Meaning, memory, and development in fuzzy-trace theory [Presidential Address]”, Judgment and Decision Making, vol. 7, no. 3, pp. 332-359, 2012.

[29] T. Betsch and A. Glöckner, “Intuition in judgment and decision making: Extensive thinking without effort.,” Psych. Inquiry, vol. 21, pp. 279-294, 2010.

[30] J.S.B.T. Evans and K.E. Stanovich, “Dual-process theories of higher cognition: Advancing the debate,” Perspectives on Psych. Science, vol. 8, no. 3, pp. 223-241, 2013.

[31] N.J. Cohen and L.R. Squire, “Preserved learning and retention of pattern analyzing skill in amnesia: Dissociation of knowing how and knowing that,” Science, vol. 210, pp. 207–209, 1980.

[32] A. Glöckner and T. Betsch, “Multiple-reason decision making based on automatic processing,” J. of Exp. Psych.: Learning, Memory, and Cognition, vol. 34, no. 5, pp. 1055-1075, 2008.

[33] A. Kiesel, W. Kunde, C. Pohl, M.P. Berner, and J. Hoffman, J. “Playing chess unconsciously,” J. of Exp. Psych.: Learning, Memory, and Cog., vol. 35, no. 1, pp. 292-298, 2009.

[34] R.E. Patterson, B.J. Pierce, H.H. Bell, and G. Klein, “Implicit learning, tacit knowledge, expertise development, and naturalistic decision making,” J. of Cog. Engineering and Decision Making, vol. 4, no. 4, pp. 289-303, 2010.

[35] A.S. Reber, “Implicit learning of artificial grammars,” J. of Verbal Learning and Verbal Behavior, vol. 6, pp. 855-863, 1967.

[36] R.E. Patterson, B.J. Pierce, A.L. Boydstun, L.M. Ramsey, J. Shannan, L. Tripp, and H. Bell, “Training intuitive decision making in a simulated real-world environment,” Human Factors, vol. 55, no. 2, pp. 333-345, 2013.

[37] K.R. Hammond, “Principle of organization in intuitive and analytical cognition (No. CRJP-231),” Colorado University at Boulder Center for Research on Judgment and Policy, 1981.

[38] D. Gergle, R.E. Kraut, and S.R. Fussel, “Using visual information for grounding and awareness in collaborative tasks,” Human Computer Interaction, vol. 28, pp. 1-39, 2013.