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Chefs Know More than Just Recipes: Professional Vision in a Citizen Science Game

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ABSTRACT

Some citizen science projects use "games with a purpose" (GWAPs) to integrate what humans and computers, respectively, can do well. One of these projects is *Foldit,* which invites talented players to predict three-dimensional (3D) models of proteins from their amino acid composition. Using Goodwin's notion of professional vision, which refers to a specialized way in which members of a professional group look at, talk about and interpret a phenomenon of interest, we investigated players' use of recipes, small scripts of computer code that automate some protein folding processes, to carry out their strategies more easily when solving game puzzles. Specifically, we examined when, how and why the players ran recipes when solving the puzzles, and what actions those recipes performed in the gameplay. Auto-ethnographic accounts produced by players at different levels of experience (beginner, intermediate, and expert) when playing the game were analyzed using a grounded theory approach. The analysis of what these players observed and revealed the professional vision necessary to use recipes sensibly and effectively. Findings highlight two key abilities: (a) repairing errors made by recipes, and (b) monitoring a large quantity of information to perform actions effectively. This study indicates that players indeed have to develop a professional vision independent of what the game itself can highlight. This is related to the nature of the game where it seems impossible for the game developers to demonstrate how players should act in the game environment because the most productive ways of acting are unknown. Players must learn to see what possibilities exist for action when confronted with a model of a protein and learn to act productively upon those possibilities. This is what we will to refer to as professional vision, which has to be acquired through active playing the game.

1. INTRODUCTION

The creation of more intelligent machines with increasing abilities opens up new modes of collaboration between humans and machines. An arena for the design of complex human-machine systems is "citizen science" or "scientific crowdsourcing" (Lintott & Reed, 2013), an approach to solving complex problems that creates novel opportunities for accelerating scientific progress by involving members of the general public. Although numerous groups work to develop software that could replace humans in activities like image recognition (e.g., Shamir et al., 2014), there are some scientific problems that are still considered computationally intractable. To solve these problems, some successful citizen science projects have developed and used "games with a purpose" (GWAPs) (von Ahn, 2006) to integrate what humans and computers, respectively, can do well. One of these projects is *Foldit,* which invites talented players to predict three-dimensional (3D) models of proteins from their amino acid composition. As skilled and talented as they can be, *Foldit* players would struggle to solve those complex puzzles without the support of machines. *Foldit* is a good example of human computation (von Ahn, 2005) since it was developed to find places where computational power is most useful and where human abilities are best applied (Cooper, 2014). Soon after the release of *Foldit*, players themselves strengthened human computation by requesting the addition of automation in the form of recipes, small scripts of computer code that automate some protein folding processes, to carry out their strategies more easily when solving puzzles. Over the years, the increasing use of recipes has created resentment in several players who think that recipes have become overused in the game and make novices think that running recipes is all they need to play the game[1]. However, previous findings (Ponti & Stankovic, 2015) suggest that the use of recipes allows skilled *Foldit* players to strengthen their role as experts rather than becoming appendages of automated gameplay.

The purpose of this study is to investigate how players at very different levels of experience with playing Foldit use recipes during their gameplay. The main research question is: What do players observe and do when they use recipes in their gameplay? To address this question, we examined the choices made by a convenience sample of three players solving two different kinds of puzzles, a beginner's puzzle and an advanced one. Specifically, we studied when, how and why the players ran recipes when solving the puzzles, and what actions those recipes performed in the gameplay. In this study, we do not embrace a notion of skill as an abstract and decontextualized entity, but we see it as an ability situated in the gameplay, which players develop by engaging actively with objects and tools within the game and the local community surrounding the game. Taking this approach means that we do not conceptualize skills as "stand-alone" cognitive processes or conceptual structures, but as abilities and forms of knowledge being performed through a network of connections-in-action involving humans and technologies. This view resonates with Goodwin's (1994) notion of professional vision, which refers to a specialized way in which members of a professional group look at, talk about and interpret a phenomenon of interest. Professional vision brings together and organizes (Goodwin, 1994):

- Gaze: ways of seeing and perceiving a phenomenon.
- Discourse: ways of talking about the observed phenomenon.
- Thinking: ways of interpreting the observed phenomenon.

[1] See "What's the point? Can't this just be automated using recipes?" and "Hand-folding vs. scripts: The Dishwasher Analogy" in Wikia *Foldit*.

- Producing artifacts: representing the knowledge produced.

Following Horstman and Chen (2012), who argued that playing a game with built-in social components such as rankings and in-game chat means participating in a specific community of practice, we also argue that playing Foldit means participating in a specific community of practice occurring through a network of connections-in-action involving humans and technologies. Horstman and Chen also suggested that a useful way of thinking about the practice of Foldit is analyzing the expert trajectories involved in playing. We build on this suggestion by arguing that in Foldit the professional vision of expert players involves the ability to see and interpret significant interactions with objects and tools in the game. This professional vision allows them to observe and assess the structure of the protein, understand when a dead end is found and when it is a good idea to take some risks in the short term for long-term advantage.

2. FOLDIT

Foldit is a GWAP developed by the Center for Game Science at the University of Washington in 2008. Players manipulate the structure of a protein in a 3D space to solve puzzle challenges and achieve the highest possible scores with a set of given tools (See Figure 1 for a screenshot). No knowledge of the scientific field that the game is based on is required, but players are expected to have several skills, especially excellent spatial awareness, the ability to take short-term risks for long-term gain, and the converse, recognizing a dead-end early and knowing when to quit (Hand, 2010).

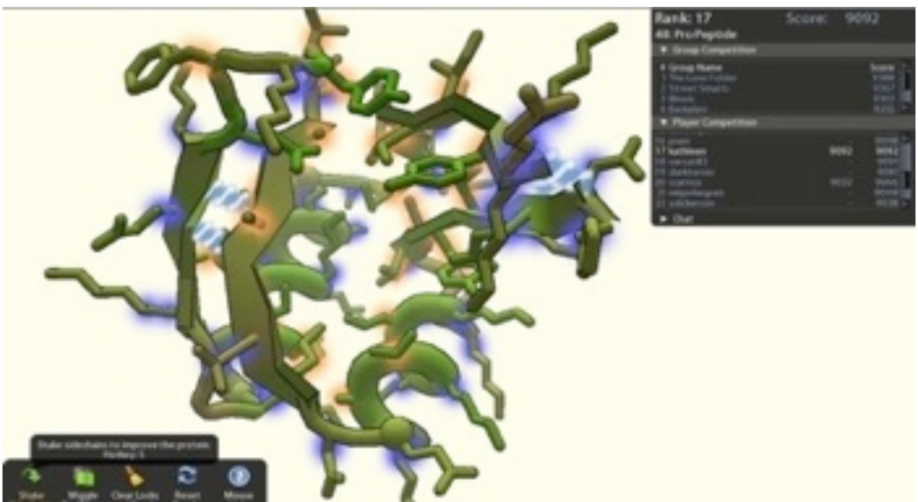

Figure 1. A screenshot of Foldit (Source: Fold.it)

The *Foldit* development team gives players the opportunity to use and write and adapt recipes to managing the increasing complexity of the game (Cooper et al., 2011). Recipes are computer programs that allow players to interact automatically with a protein and repeat simple routines consistently, or perform a series of complex routines which keep running in the background forever. Using recipes is one of the easiest ways to get to the top and, reportedly, most top players are using them to some extent (Ponti & Stankovic, 2015).

3. METHODS

3.1 Issues in the Study of Players' Professional Vision

Players' professional vision allows observing and assessing the structure of the protein, understanding when a dead end is found and when they can take some risks in the short term for long-term advantage. The study of players' professional vision posed some practical challenges. These practical challenges influenced our methodological choices and the research question. We had to balance methodological demands under the conditions of limited access to data. First, because of competitive reasons we were not allowed logging and accessing real-time data from gameplay. Second, gaining access to and recruiting potential research participants was also challenging because they were hard-to-reach. Several potential participants (contacted initially through the built-in mail in *Foldit*) did not respond to recruitment efforts either because of a general lack of interest or because they no longer played the game. Over a year of exploring the game, through reading online discussions in the game forum and documents in *Wikia Foldit*, and interviewing a small group of players in a previous study (Ponti & Stankovic, 2015), we finally managed to establish rapport with a top-ranked player. This expert player has invested a lot of time on playing the game, has handfolded proteins without using many recipes for at least two years and has moved beyond simple competence to achieve high positions in the game ranking leagues. Third, playing *Foldit* involves a steep learning curve. It takes a lot of effort and time. Although one of the authors, Stankovic, played the game at a beginner's level to acquire a basic understanding of the gameplay (about 50 hours of play), it was soon clear it would take him an inordinate number of hours to function as the intermediate player. Since we were interested in studying professional vision at different levels of expertise, we kept Stankovic as a beginner and we relied on the top player to help us gain access to an intermediate player who is a member of his team. This player had also played for two years, investing much time and computer power to be not too far behind the top players.

The three players (beginner, intermediate and expert) were a purposive sample which allowed focusing on their respective abilities when playing the game. We considered player ability the characteristic that would best enable us to answer our research question.

3.2 Data Collection and Analysis

We asked the players to conduct autoethnography (Brown, 2015) on their playing of the puzzles. All three players played one beginner puzzle. Furthermore, we asked the expert player to keep a detailed record of his gameplay of one advanced puzzle. Both puzzles were De-novo puzzles in which only the primary sequence (series of amino acids) of a protein is known at the start. The peptide (chain) is provided as a straight string which players need to analyze and fold. The goal is to get close to a native low energy folded protein. Many strategies are provided by players to start this type of puzzles in tutorial pages and videos.

We asked the players to record their gameplay, if possible, and write detailed, first-hand accounts of their play. We chose this approach to be able to examine three accounts at different levels of expertise and knowledge of the game.
Our unit of analysis was the observable interaction between players and their game space in the puzzles. The observation was informed by the concept of professional vision, as we looked at what players observed, did and thought (when thinking was made explicit and therefore became "observable") at different stages of the game and how they performed their actions, the actions performed by recipes and the outcomes of these actions. We also looked at the external sources of information used by the players. By external sources (as opposed to internal cognitive resources such as experience and intelligence) we refer to all the visual tools used by *Foldit* to convey information to players. The game interface displays text and numbers and contains many buttons and commands to interact with the game (see Figure 1).

The autoethnographic descriptions, including text, videos, and screenshots, provided the opportunity to "see" how players described their playing and understood the unfolding of events in the game space. From these accounts, we could infer their ability to see and interpret significant interactions with objects and tools in the game. The data corpus used in this study consists of four autoethnographic descriptions as is summarized in Table 1. We analyzed all the data collected using a grounded theory approach (Charmaz, 2006).

Player	**Puzzle for Beginners (<150): Easy Mini Freestyle**	**Advanced Puzzle: De-Novo FreeStyle 58**
Igor (IS) – beginner	Video recorded and journaled 6:06 minutes before abandoning the game	
Lyn (LB) – intermediate	Journaled completion of the puzzle in 24 hours, including overnight recipes when she was off.	
Bruno (BK) – expert	Video recorded when he was present and paused when running recipes and he was off: total 16 minutes of man work and about 3-4 days of computer work.	Journaled 498 minutes of man work (= about 8 hours) plus 60 minutes of editing a recipe. 6,5 days of computer work on a mean of about 3 tracks = about 468 hours of computer time. The final result was achieved with about 2% of human resources and 98% of computer (recipes) work.

***Table 1.** Summary of collected data*

4. RESULTS

For the sake of brevity, we only report the frequencies of the actions observed in the accounts provided by the three players and the frequencies of external sources of information they used. Readers can find detailed narratives of the actions performed by the players in Ponti, Stankovic, Barendregt, Kestemont, and Bain (2017).

4.1 Puzzle for Beginners: Easy Mini Freestyle

In the three accounts, the players described different strategies to solve the same puzzle and, accordingly, their selection criteria for running recipes varied. Figure 2 summarizes the results of the axial coding analysis related to the most frequent actions performed by players in association to "running a recipe."

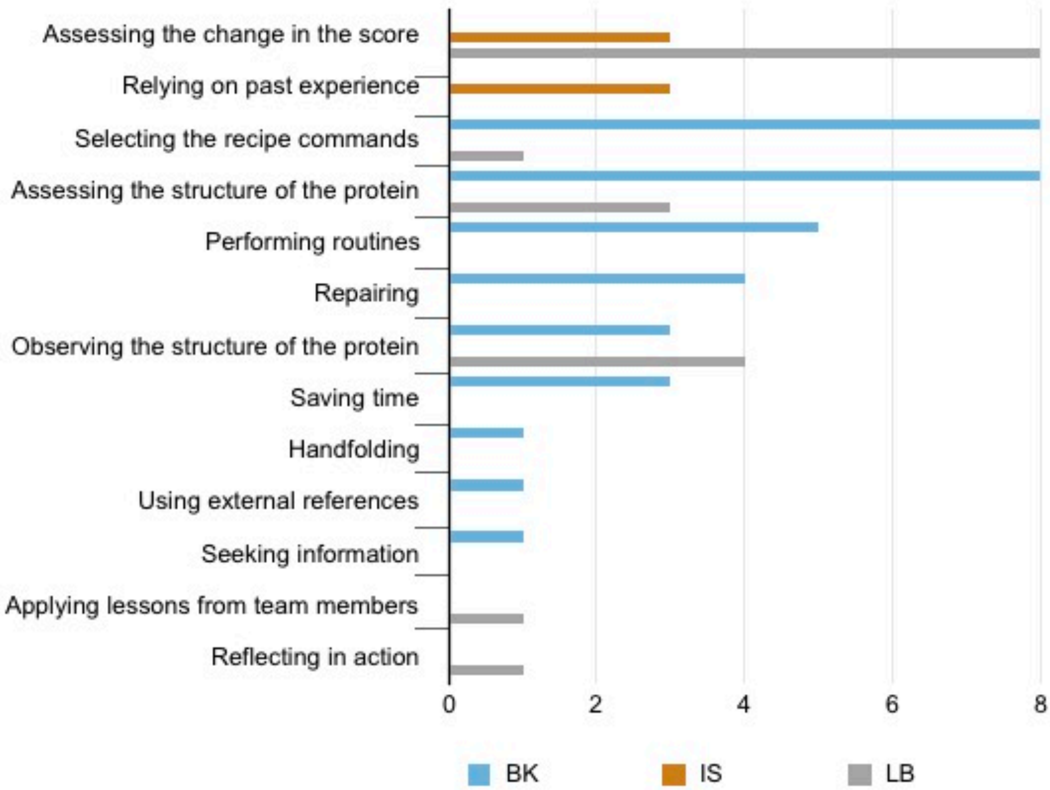

Figure 2. ***Observed actions associated to run a recipe in the puzzle for beginners***

The chart indicates that assessing and observing the structure of the protein are central categories in the gameplay of BK, the expert player. The difference between the two actions can be articulated as follows: observation provides a picture of what the player sees, while an assessment is an evaluation of what has been observed, including ideas of what could be done to improve the structure protein. Repairing the

errors made by recipes is also an action performed only by BK, the expert player. The chart indicates that the two less experienced players, IS (beginner) and LB (intermediate), are more concerned with assessing the output of their actions, including running recipes, on the score.
Figure 3 shows the occurrences of external sources of information used by the three players when performing the actions shown in Figure 3.

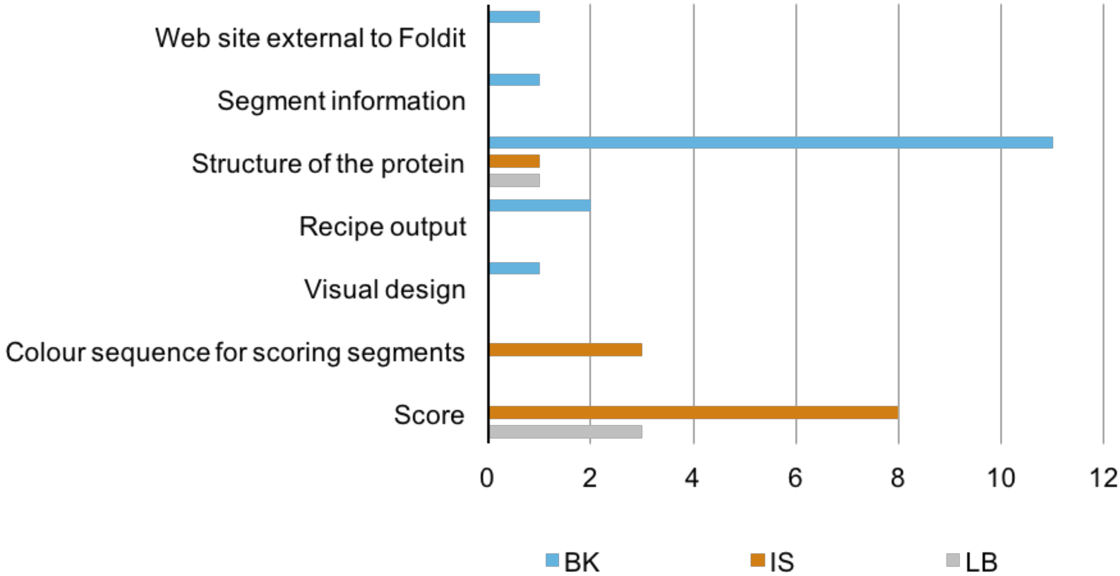

Figure 3. Most frequently used external sources of information

The chart indicates that the score was the most important source of information for the beginner (IS), and to some extent for the intermediate player (LB) as well. IS reported that, given his limited experience with the game, he felt unsure of the output of his actions and the score was the main indicator of whether he was doing something correctly or not. By contrast, the structure of the protein was the most important source of information for BK, the expert player, as he had already developed a specialized way of "seeing" it and identifying meaningful events in the structure of a protein.

4.2 **Advanced Puzzle> De-Novo FreeStyle 58**

Figure 4 summarizes the results of the axial coding analysis related to the most frequent actions performed by BK, the expert player, in association to "running a recipe."

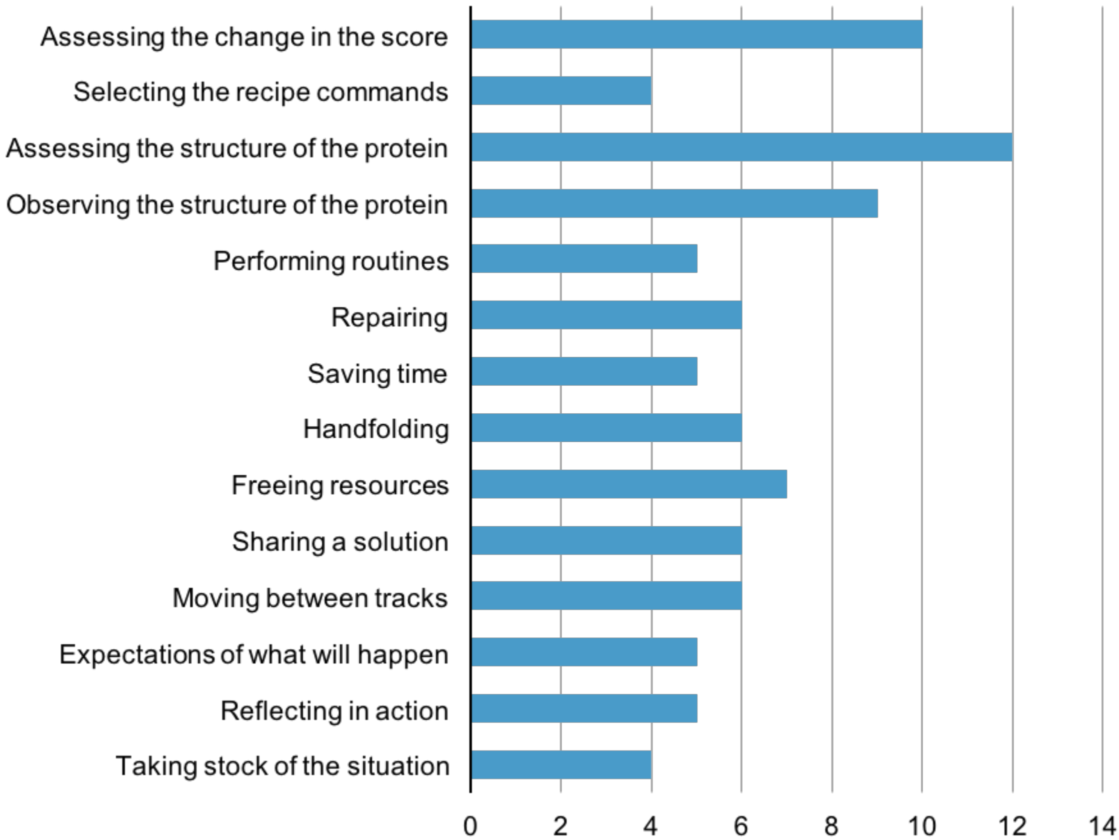

Figure 4. Observed actions associated with running a recipe in the advanced game

Since the expert player played this puzzle in a competitive mode (unlike the puzzle for beginners, where he was not involved in a competition), assessing and observing the structure of the protein and assessing the change in the score were his most recurrent actions.

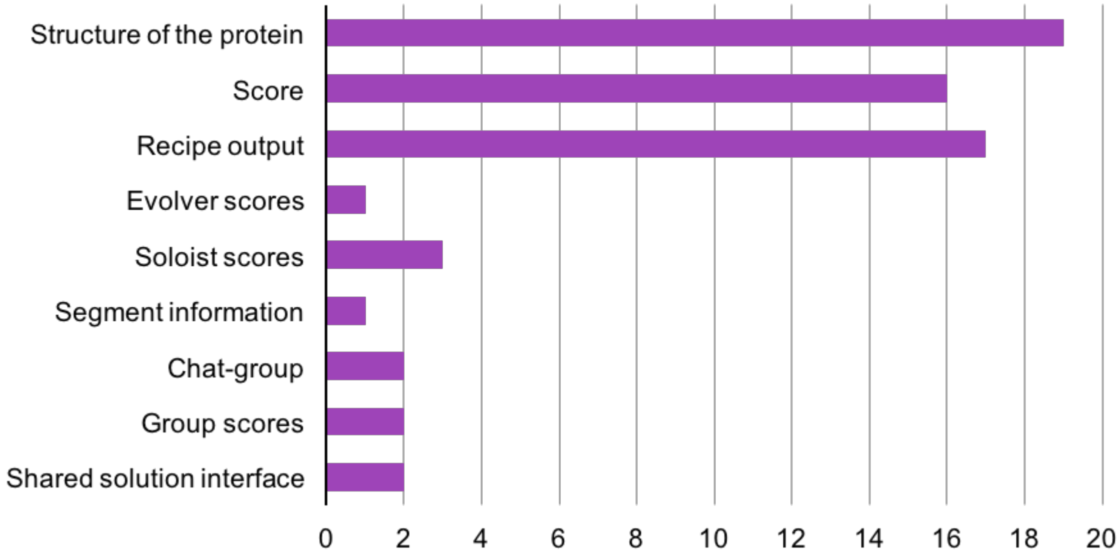

***Figure 5.* Most frequently used external sources of information**

Figure 5 shows the occurrences of the external sources of information used by the expert player (BK) when performing the actions shown Figure 4. The structure of the protein, the score, and the recipe output were the three sources used most frequently for deciding to run a recipe.

5. DISCUSSION AND CONCLUSION

Inspired by Goodwin's (1994) notion of professional vision, we conceptualized and studied skills as abilities and forms of knowledge being performed through a network of connections-in-action involving humans and technologies. Thereafter, we looked at *Foldit* players' practices of seeing and organizing their gameplay, because analyzing the trajectories involved in playing the game, especially the expert gaming practice, is a useful way to gain an understanding of expertise with this game.

Our findings highlight two key abilities:

(a) repairing;

(b) monitoring a large quantity of information to perform actions effectively.

5.1 Repairing

Recipes perform actions for a long time to get players closer to their goals. For example, they can fix errors made by other recipes. However, repairing errors is not just a computational action but involves human judgment. Figure 2 shows that repairing the errors made by recipes is an action performed only by the expert player. While experienced players know how to run recipes at proper stages of the gameplay – for example, they may spend time to handfold at the beginning of the puzzle and then run local optimize scripts as the game progresses (Cooper, 2014) – and have a good idea of what a natural protein would look like, beginners need to develop this competence. As also suggested by the results of a study on the way recipes influence gameplay and the human understanding of the game in Foldit, based on interviews with players (Ponti & Stankovic, 2015), experience is an intervening condition bearing upon competence to use recipes effectively. Recipes can have serious limitations in relation to designing and predicting the structure of a protein. This is why it is necessary to develop competence about what recipes can and cannot do. While recipes can help detect good shapes and allow players to make rapid progress to the solution of puzzles, they are also said to do little to fix fundamental flaws which require intelligent intervention, something that is notoriously difficult to do with software (Ponti & Stankovic, 2015).

5.2 **Monitoring Large Quantities of Information**

A skilled player can monitor a large quantity of information to make effective decisions, including running recipes. To a beginner, the many sources of information available in and through the game interface seem complex and opaque. The novice is less capable of monitoring this complexity and progress in the game. What appears as a jumble of numbers, text and protein movements to the beginner, becomes slowly understandable to the intermediate player, and is familiar to the expert. The skill of monitoring this great intake of information entails the ability to make sense of information – for example, the stream of data produced by recipe outputs – and reflect upon the significance for setting goals and taking further actions. A player who has not developed this skill – such as our beginner – just engages with a puzzle, moves through it and acts in it, without being able to coordinate the information provided by the many external sources of information and focusing mainly on the score. Interpreting the meaning of the score in *Foldit* is only apparently intuitive since the score is a sum of the scores of each segment of the structure of a protein, plus 8000. Nevertheless, less experienced players can see the score as a more straightforward form of information than the structure of the protein.

Monitoring large quantities of information from different sources involves the selective use of specific information to perform certain tasks at different stages of the game. Our findings indicate that the expert player – and to a less extent the intermediate one – knows how to manage specific sources of information at different stages. They have learned how to change strategies if they do not meet their goals, use time more efficiently, assess the outcomes of recipes and choose future recipes based on what they have experienced before. Experienced players know how to combine scripts and hand-folding at the right time, perhaps abandoning good scoring solutions when they do not look visually nice. However, experts also run good scoring solutions in parallel because sometimes this is the only way to rank well. Conversely, the beginner relies mostly on random actions, although the expert and the intermediate also perform some random tries. When players face a new challenge, try a new recipe, or have abundant computational resources to work with, they use random actions. To conclude, although recipes embed a number of simple, time-consuming and repetitive manual actions, they cannot yet replace the human skills needed to address the complexity of the game. Repairing and monitoring a great quantity of environmental information are capabilities that humans learn over time, through training and playing the game intensively. They cannot be achieved through the rote application of recipes.

6. **LIMITATIONS**

This study is based on a non-random purposeful sample because we looked for particular cases to address our research question. Therefore, it cannot be considered representative of the larger population of Foldit players, and the results cannot be generalized. Arguably, our results are somehow biased towards the players who actually are committed to playing the game and interested in helping researchers investigate the role of professional vision in gameplay. We are also aware that our results are based on the analysis of a single game. Future research exploring further professional vision in citizen science game projects could improve theory and practice and help generalize the results of this study.

7. ACKNOWLEDGMENTS

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