Understanding Learning Behaviours in

Playing Sorting Algorithm Game

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*Abstract*—Based on our previous work, our gamification of sorting algorithm learning has been able to support learners to produce better learning outcomes if we compare them to the performance when they learn only in a traditional way – using textbooks. However, the finding does not reveal any specific explanation on how the result could happen. In this research, we make effort to identify several learning behaviours and examine to what extent they can lead learners to successful learning outcomes. Therefore, we extract several variables as the representation of the learning behaviours or outcomes from the event logs. We then use Kendall’s Tau to calculate the correlations between the variables. We found out that allocating efforts on understanding the algorithms didactically, paying attention to the demo or illustration, spending more time playing, and exerting more attempts to complete the levels correlate significantly and positively with varying magnitudes to the completeness and number of completing the levels.

Keywords—learning analytics, game analytics, gamification, learning behaviours, sorting algorithms

# Introduction

Along with the growth of digital games, Game Analytics [1] also emerges as a field that draws a large amount of attention from professionals, industries, and academia to gain deeper insights from the occurring behavioural patterns from the interaction between games and their players. Games or game elements are also applied for serious purposes other than leisure. Specifically, in the field of education, gamification – the process of transforming a less gameful entity to be more gameful [2][3] – has been actively researched, developed, and applied in the learning processes to improve learners’ motivation and engagement. However, there are a limited number of studies that report the use of game analytics to understand learners’ learning behaviours during their interaction with gameful learning artefacts and reflect on it using learning theories’ point of views. Therefore, we also view our study as an opportunity to position our Game Analytics as a Learning Analytics [4], which is also known as Serious Game Analytics [5], to gain insights from the learning behaviours of the players of Serious Games [6].

This study essentially is a follow-up research of our previous work on developing and evaluating the artefact of gamification of sorting algorithm learning, Sort Attack. From our previous studies, we identified that our gamification of sorting algorithm learning could support our students to perform better if we compare their performances to the traditional mode of learning—learning only from textbooks [7]. Moreover, the satisfying result of the gamification raised our curiosity on how the gamification actually works thus motivates to find the underlying variables, processes, and structures of how the gamification works. Based on our preliminary work, using a graph visualisation, we figured out that a learner exhibited several learning patterns, including their own strategies in dealing with difficult challenges, during their interaction with the gameful artefact in learning sorting algorithms [8]. Identification of the patterns and their correlations to some variables of successful learning outcomes can lead us to understand better the behaviours that predict successful learning outcomes, which an effective learning strategy can be derived from.

The followings are the organisation of this paper. First, we begin our paper with an introduction to the background and motivation of our work. Next, we briefly explain some related works to position our study in the context of the Game-Learning Analytics related research. Subsequently, we describe the method used in our research. Afterward, we present and discuss our findings. We then close our paper with conclusions and propose some design implications based on our findings.

# Related Works

Educational bodies can apply Learning Analytics to support students to succeed in their education [9]. Learning Analytics applies the data-intensive approaches to educational research for the goal of improving educational practice [10]. Gašević *et al*. emphasise that learning analytics is about learning [11]. Therefore, there should always be something valuable that contributes back to the body of learning. A related example is the work of White and Larusson that tried to leverage the value of originality in student writing [12]. We expect our study to do the same as well as contributing to the understanding that some learning behaviours correlates to some learning outcome variables, which from the understanding, an effective learning strategy is derived.

Many Learning Analytics research put much attention on understanding learning behaviours, which our research also does. For example, Phillips *et al.* explore Learning Analytics as the indicators of learning behaviours [13]. Also, for the domain of open-ended programming tasks, Bilkstein *et al.* use Learning Analytics to evaluate students’ behaviours [14]. Furthermore, Wolff *et al.* analyse clicking behaviour in a virtual learning environment to predict at-risk students to improve retention [15]. Masip *et al.* proposed an algorithm to model learners’ behaviours in navigating a virtual campus. They transformed learners’ event logs into adjacency matrixes—indicating their transition between regions in the virtual campus, clustered the matrixes, and then visualised the matrix clusters into graphs [16]. Moreover, Agudo-Peregina *et al.* tried the use of classification of interactions to predict success in VLE-supported F2F and online learning [17]. Another related study is the work of Fortenbacher *et al.* based on development of LeMo tool, which employs User Path Analysis and Interactive Visualisation as the main methods for their Learning Analytics [18]. However, it is to be noted that all of these works are not conducted in the context of Serious Games that might give different effects on how students learn.

On the other hand, Game Analytics has been used widely to gain insights into player behaviours, game production, and game performance. However, getting insights into player behaviours draws much more attention than the other two [19]. An example is the work of Drachen *et al*. of clusters players’ behaviours in computer games [20]. Since some of the available games now are not solely used for leisure purpose but also for learning a.k.a. Serious Games, there has been a rise in Serious Game Analytics as well. Hauge *et al.* investigated the learning analytics’ implications for serious game design. They proposed two modes of analytics which are the offline (post-game) analytics and real-time (in-game) analytics [21]. Regarding the two ways of analytics, our research used the offline post-game analytics. Callaghan *et al*. employed game analytics to measure student engagement/retention in the environment of engineering education [22]. Moreover, Hicks *et al.* utilised game analytics to evaluate level progression and puzzle design in a serious game [23]. By working on log data extracted from a rational-number-addition game, Kerr and Chung did apply cluster analysis to identify key features of learning behaviours thereby representing the keys in the form of error patterns and strategies of solution to for every level [24]. Furthermore, using the visualisation, Liu *et al.* examined what tools the learners accessed as they engaged in a middle school science serious game [25].

Based on our literature review, we differentiate our work from the other existing works on several aspects. First, the domain of our work is specific on algorithm learning, which has not been covered by the previous studies. The unique aspect of learning algorithms demands more understanding on how an algorithm works rather than memorising every single step of the algorithm. This enables the application of the principles of the respective algorithm when problems become more complex. Second, none of the previous works have investigated the after-failure strategies when playing a sorting algorithm learning game and their relationships to learning outcomes. Our research addresses this question while also investigating some learning efforts variables and their relationships to learning outcomes. We have also developed a gamification of sorting algorithm learning that is similar to the learning application developed by Boticki *et al*. [26]. However, we view that our gamification incorporates more gameful characteristics as they only implement points and leaderboard as their game elements.

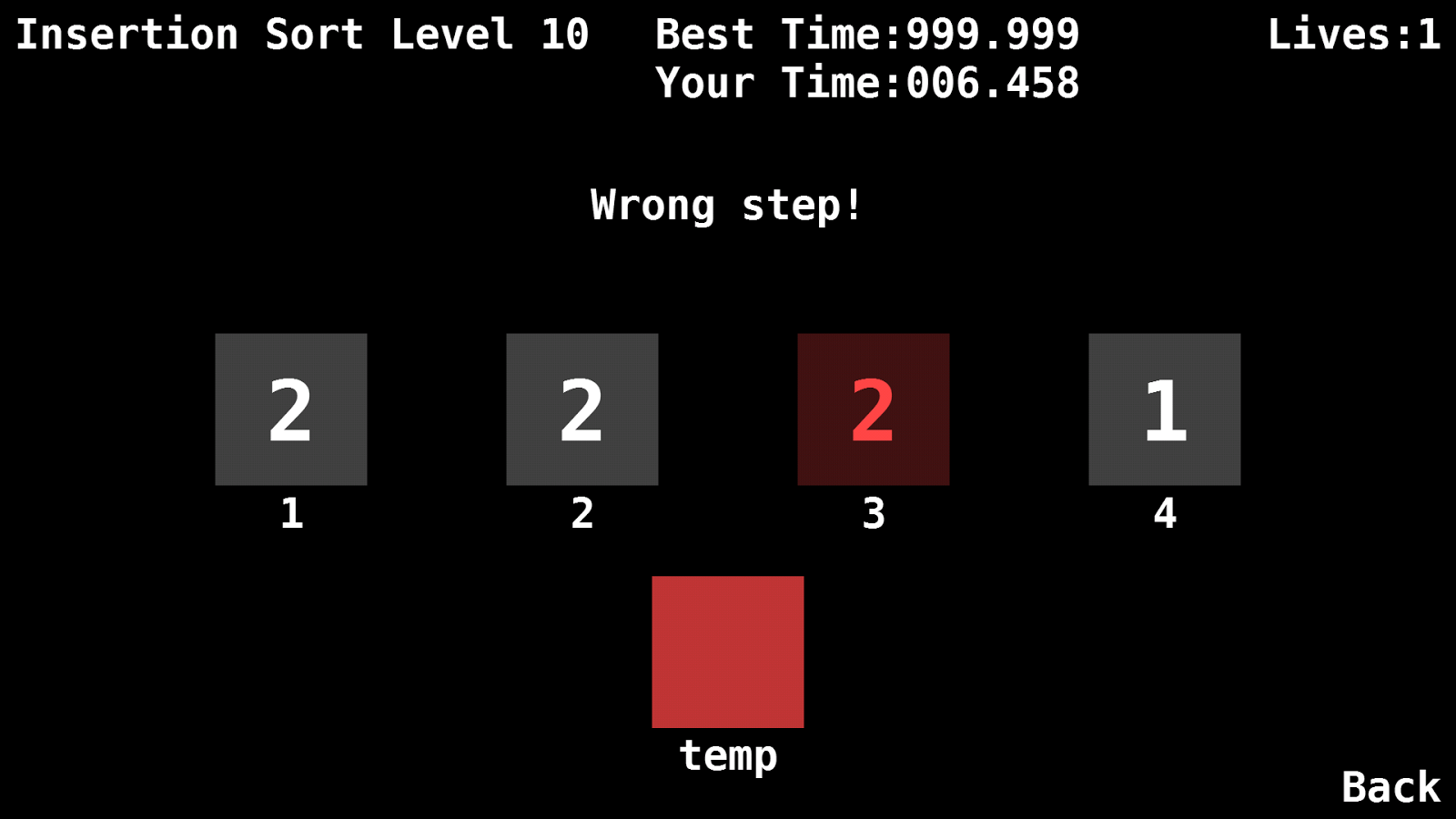


Fig. 1. Sort Attack: Gamification of Sorting Algorithm Learning [7].

# Research Method

Sort Attack is a gamification of sorting algorithm learning designed to teach insertion sort, selection sort, and bubble sort to the first-year computer science students when they are introduced to algorithms for the first time. The artefact incorporates several game elements that are common in many games, such as levels, challenges, rules, and feedbacks to maintain the engagement and motivation of the students. For the game mechanics, a player will be given a set of boxes with a value inside each of them and a temporary box. To complete a level, the player needs to imitate the execution of the selected sorting algorithm by dragging and dropping the boxes. As the player progresses, the game becomes more difficult—the combination of the values changes and the number of the boxes together with the digit of the values increases. The player has three game-lives which afforded them three chances for continuation after making mistakes. Other than that, the player has to replay the level. Fig. 1 shows a screenshot of an incorrect step in executing insertion sort algorithm in Sort Attack.

We have tested Sort Attack to computer science, informatics, or information technology students with the details of the test method explained in our previous work [7]. We have performed three instances of the test at three different universities to support the generality of our findings. In brief, the test was a controlled experiment consisting of two sessions and two groups of students. At the first session, a group learned sorting algorithms using textbooks only as the resources of their learning materials and a group that used Sort Attack as their learning tool. After a 15-minute learning, they were asked to solve sorting algorithms problems. After a while, they were requested to change their mode of learning and were given further 15 minutes to study the sorting algorithms before they were again asked to solve other sorting algorithms problems. We report the result of the first test in our previous publication [7].

Before ending the test, students were asked to upload their event logs using the upload log feature inside Sort Attack (Fig. 2 shows a sample format of the event logs). We explained that the logs will be useful for our further research, but they were not obligated. After two months, 60 log files were uploaded. Next, we reviewed the log’s size; we decided to remove two logs from our collection since the size is too small and no significant information was contained in the logs, leaving us with 58 log files to study. The format of the log was explained in our other previous work [8] with every line record containing information on the state, activity, and time of the event. From the log, we can reconstruct a graph of how a learner plays the artefact and also identify sixteen attributes that can be associated to measure the behaviours and performance of a learner’s learning processes.

We assume a log file is a representation of a learner who played with the artefact since the log file recorded the person’s activities with the artefact. A change in one of the attributes of the person’s interaction with the artefact might have certain relationships with the changes in other attributes. Therefore, we use correlation approach to identify the relationships between the attributes. We use the 58 learners as the number of measurements required for the correlation calculation. We proceeded to do a normality test using the Shapiro-Wilk test [27] on every attribute and identified that not all attributes have a normal distribution. Consequently, we used Kendall’s Tau [28] to calculate the correlation between the attributes.

# Results and Discussions

## The Attributes of Learners’ Learning Behaviours and Their Grouping

Based on the game logs collected, we have successfully identified sixteen attributes that we classified into three groups: After-Failure Strategies, Learning Efforts, and Learning Outputs. The attributes can be used to describe learners’ learning behaviours and to measure their learning outputs during their interactions with the artefact.

**After-Failure Strategies** are the strategies used by learners to overcome their difficulties or failures in completing certain levels. We assume that it is important to understand which strategy is most effective to determine the success of learners to perform well in learning. Therefore, we have identified six after-failure strategies as follows: Theoretical Resolution (THR): Revisit the Introduction (Level 1) after failure, striving to understand the intended algorithm through theoretical explanation. Demonstrative Resolution (DER): Return to Tutorial (Level 2) after failure, endeavouring to understand the intended algorithm through watching demos. Repetitious Resolution (RPR): Replay the level after failure, striving to complete the intended level through replay. Retreating Resolution (RTR): Return to the previous level after failure, striving to complete a difficult level through learning from the previous level. Cross-Algorithm Resolution (COA): “Give up!” Leave the difficult level without completing it and *move to another different type of algorithm*. Leaving-Off Resolution (LOA): Another type of “Give up!” in which learners decided to *move on to a higher level* *but still on the same type of sorting algorithm* without completing the troublesome level, which differentiates LOA from COA.

**Learning Efforts** are the efforts exerted by learners to learn algorithms and accomplish levels. These attributes indicate whether the learners used much or less time and tried to complete the levels. We have identified four attributes as follows. Theoretical Effort (THE): The number of how many times learners start the Introduction (Level 1) to learn algorithms through theoretical explanation. Demonstrative Effort (DEE): The number of how many times learners start the Tutorial (Level 2) to learn algorithms through watching demos. Playtime (PLT): The duration (time) the learners spent to accomplish levels. Number of Attempts (NAT): The number of how many times learners start playing any levels.

|  |  |  |
| --- | --- | --- |
| **Id** | **Timestamp** | **Label** |
| 001 | 18032015102433 | Insertion Sort Level 13: Level Started |
| 001 | 18032015102436 | Insertion Sort Level 13: Fail - Dropped box 2 to box holder -1, dropped box 1 to box holder -1 expected, Lives = 2 |
| 001 | 18032015102438 | Insertion Sort Level 13: Success - 1 to -1 |
| 001 | 18032015102439 | Insertion Sort Level 13: Fail - Dropped box 1 to box holder 2, dropped box 2 to box holder 2 expected, Lives = 1 |

Fig. 2. A sample format of event log generated in Sort Attack [8].

**Learning Outputs** are the attributes that we perceive as the outputs resulting from the learner’s interaction with the game, which can be used to measure the achievement of their learning processes. The followings are the attributes. Number of Game-Overs (NGO), the number of how many times learners experienced Game Over. Number of Errors (NER): The number of how many times learners experienced failures performing the wrong steps. Number of Completions (NCO): The number of how many times learners completed a level. Completeness (CMP): The number of how many different levels completed. There are maximum 96 levels available to complete for all the three sorting algorithms, 32 levels each. Error Rate (ERR): The ratio between the number of how many times learners did wrong steps and the number of how many times learners start playing any levels (ERR = NER / NAT). Success Rate (SUR): The ratio between the number of how many times a learner completes any level and the number of how many times the learner starts playing any level (SUR = NCO / NAT).

## Findings and Discussions

Based on Kendall’s Tau Correlations between the attributes of learners’ learning behaviours in TABLE 1, we found some interesting findings that enlighten us on how learners learn algorithms through playing games. We discuss the results in the following paragraphs.

Success Rate (SUR) has significant positive weak correlations with the Number of Completions (NCO) and the Completeness (CMP). The interpretation of this finding is that more successes in completing levels or more levels completed indicate a slight increase in success rate. However, playing many times (NAT) or spending more time (PLT) with the artefact does not necessarily predict an increase in Success Rate (SUR). The reason is that learners also experience failures, not only successes, during the learners’ playtime (PLT) and attempts (NAT). Using the playtime and efforts to learn the theories (THE) and viewing the demos (DEE) does not necessarily indicate an increase in Success Rate (SUR) since the playtime (PLT) and attempts (NAT) are used to learn and are not used to complete any levels successfully. Error Rate (ERR) has a significant negative weak correlation with Success Rate (SUR). Thus, an increase in Error Rate (ERR) will indicate a decrease in Success Rate (SUR). The After-Failure Resolutions—the Theoretical Resolution (THR), Repetitious Resolution (RPR), and Cross-Algorithm Resolution (CAR)—strengthen these reasons. They show significant negative weak to moderate correlations towards the Success Rate, but indicate significant positive moderate relationships towards the Error Rate in opposition.

Completeness (CMP) has a significant positive very strong correlation with the Number of Completions (NCO). Therefore, a learner who completed all or most of the levels tends to have a high Number of Completions (NCO) and vice versa. Every attribute of Learning Efforts has a significant positive relationship to Completeness (CMP): a moderate degree of Theoretical Effort (THE) and a strong degree of Number of Attempts (NAT), with the latter has the strongest relationship with Completeness (CMP). These relationships mean that every learning effort exerted will give a significant positive contribution for a learner to complete most or all of the levels. However, the Number of Attempts (NAT) is the strongest predictor to successfully complete the game.

|  | **After-Failure Strategies** | | | | | | **Learning Efforts** | | | | **Learning Outputs** | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **THR** | **DER** | **RPR** | **RTR** | **LOA** | **COA** | **THE** | **DEE** | **PLT** | **NAT** | **NGO** | **NER** | **NCO** | **CMP** | **ERR** | **SUR** |
| **THR** | 1.000 | 0.131 | .477\*\* | 0.098 | 0.220 | .310\*\* | .488\*\* | .252\* | .281\*\* | .481\*\* | .466\*\* | .538\*\* | .320\*\* | .319\*\* | .298\*\* | -.234\* |
| **sig.** |  | 0.255 | 0.000 | 0.345 | 0.051 | 0.003 | 0.000 | 0.013 | 0.003 | 0.000 | 0.000 | 0.000 | 0.001 | 0.001 | 0.002 | 0.014 |
| **DER** | 0.131 | 1.000 | 0.135 | 0.200 | 0.070 | 0.155 | .298\*\* | .359\*\* | 0.189 | .270\* | 0.161 | .217\* | 0.189 | 0.125 | 0.020 | -0.083 |
| **sig.** | 0.255 |  | 0.230 | 0.093 | 0.588 | 0.199 | 0.007 | 0.002 | 0.084 | 0.013 | 0.151 | 0.047 | 0.083 | 0.257 | 0.858 | 0.445 |
| **RPR** | .477\*\* | 0.135 | 1.000 | .255\* | .320\*\* | 0.174 | .399\*\* | .210\* | .381\*\* | .442\*\* | .513\*\* | .562\*\* | .258\*\* | .220\* | .361\*\* | -.332\*\* |
| **sig.** | 0.000 | 0.230 |  | 0.012 | 0.004 | 0.090 | 0.000 | 0.033 | 0.000 | 0.000 | 0.000 | 0.000 | 0.006 | 0.018 | 0.000 | 0.000 |
| **RTR** | 0.098 | 0.200 | .255\* | 1.000 | .269\* | .377\*\* | 0.149 | .270\*\* | .282\*\* | .253\* | .557\*\* | .504\*\* | .263\*\* | .233\* | .378\*\* | 0.020 |
| **sig.** | 0.345 | 0.093 | 0.012 |  | 0.021 | 0.001 | 0.137 | 0.010 | 0.004 | 0.010 | 0.000 | 0.000 | 0.008 | 0.019 | 0.000 | 0.839 |
| **LOA** | 0.220 | 0.070 | .320\*\* | .269\* | 1.000 | .302\* | .258\* | 0.175 | 0.047 | .266\* | .445\*\* | .392\*\* | 0.130 | 0.094 | .301\*\* | -0.121 |
| **sig.** | 0.051 | 0.588 | 0.004 | 0.021 |  | 0.011 | 0.017 | 0.123 | 0.657 | 0.013 | 0.000 | 0.000 | 0.225 | 0.380 | 0.005 | 0.257 |
| **COA** | .310\*\* | 0.155 | 0.174 | .377\*\* | .302\* | 1.000 | .295\*\* | 0.125 | 0.074 | .220\* | .486\*\* | .435\*\* | 0.113 | 0.088 | .390\*\* | -.210\* |
| **sig.** | 0.003 | 0.199 | 0.090 | 0.001 | 0.011 |  | 0.003 | 0.237 | 0.460 | 0.027 | 0.000 | 0.000 | 0.259 | 0.382 | 0.000 | 0.035 |
| **THE** | .488\*\* | .298\*\* | .399\*\* | 0.149 | .258\* | .295\*\* | 1.000 | .551\*\* | .421\*\* | .638\*\* | .304\*\* | .399\*\* | .459\*\* | .394\*\* | 0.015 | -0.166 |
| **sig.** | 0.000 | 0.007 | 0.000 | 0.137 | 0.017 | 0.003 |  | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 | 0.866 | 0.070 |
| **DEE** | .252\* | .359\*\* | .210\* | .270\*\* | 0.175 | 0.125 | .551\*\* | 1.000 | .409\*\* | .600\*\* | 0.147 | .280\*\* | .583\*\* | .524\*\* | -0.124 | 0.073 |
| **sig.** | 0.013 | 0.002 | 0.033 | 0.010 | 0.123 | 0.237 | 0.000 |  | 0.000 | 0.000 | 0.134 | 0.004 | 0.000 | 0.000 | 0.195 | 0.445 |
| **PLT** | .281\*\* | 0.189 | .381\*\* | .282\*\* | 0.047 | 0.074 | .421\*\* | .409\*\* | 1.000 | .595\*\* | .228\* | .381\*\* | .584\*\* | .528\*\* | 0.022 | 0.080 |
| **sig.** | 0.003 | 0.084 | 0.000 | 0.004 | 0.657 | 0.460 | 0.000 | 0.000 |  | 0.000 | 0.014 | 0.000 | 0.000 | 0.000 | 0.804 | 0.376 |
| **NAT** | .481\*\* | .270\* | .442\*\* | .253\* | .266\* | .220\* | .638\*\* | .600\*\* | .595\*\* | 1.000 | .339\*\* | .511\*\* | .739\*\* | .678\*\* | 0.045 | -0.016 |
| **sig.** | 0.000 | 0.013 | 0.000 | 0.010 | 0.013 | 0.027 | 0.000 | 0.000 | 0.000 |  | 0.000 | 0.000 | 0.000 | 0.000 | 0.619 | 0.862 |
| **NGO** | .466\*\* | 0.161 | .513\*\* | .557\*\* | .445\*\* | .486\*\* | .304\*\* | 0.147 | .228\* | .339\*\* | 1.000 | .801\*\* | .202\* | .200\* | .680\*\* | -.199\* |
| **sig.** | 0.000 | 0.151 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.134 | 0.014 | 0.000 |  | 0.000 | 0.030 | 0.032 | 0.000 | 0.032 |
| **NER** | .538\*\* | .217\* | .562\*\* | .504\*\* | .392\*\* | .435\*\* | .399\*\* | .280\*\* | .381\*\* | .511\*\* | .801\*\* | 1.000 | .369\*\* | .358\*\* | .536\*\* | -0.141 |
| **sig.** | 0.000 | 0.047 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.004 | 0.000 | 0.000 | 0.000 |  | 0.000 | 0.000 | 0.000 | 0.121 |
| **NCO** | .320\*\* | 0.189 | .258\*\* | .263\*\* | 0.130 | 0.113 | .459\*\* | .583\*\* | .584\*\* | .739\*\* | .202\* | .369\*\* | 1.000 | .891\*\* | -0.066 | .249\*\* |
| **sig.** | 0.001 | 0.083 | 0.006 | 0.008 | 0.225 | 0.259 | 0.000 | 0.000 | 0.000 | 0.000 | 0.030 | 0.000 |  | 0.000 | 0.464 | 0.006 |
| **CMP** | .319\*\* | 0.125 | .220\* | .233\* | 0.094 | 0.088 | .394\*\* | .524\*\* | .528\*\* | .678\*\* | .200\* | .358\*\* | .891\*\* | 1.000 | -0.059 | .296\*\* |
| **sig.** | 0.001 | 0.257 | 0.018 | 0.019 | 0.380 | 0.382 | 0.000 | 0.000 | 0.000 | 0.000 | 0.032 | 0.000 | 0.000 |  | 0.519 | 0.001 |
| **ERR** | .298\*\* | 0.020 | .361\*\* | .378\*\* | .301\*\* | .390\*\* | 0.015 | -0.124 | 0.022 | 0.045 | .680\*\* | .536\*\* | -0.066 | -0.059 | 1.000 | -.262\*\* |
| **sig.** | 0.002 | 0.858 | 0.000 | 0.000 | 0.005 | 0.000 | 0.866 | 0.195 | 0.804 | 0.619 | 0.000 | 0.000 | 0.464 | 0.519 |  | 0.004 |
| **SUR** | -.234\* | -0.083 | -.332\*\* | 0.020 | -0.121 | -.210\* | -0.166 | 0.073 | 0.080 | -0.016 | -.199\* | -0.141 | .249\*\* | .296\*\* | -.262\*\* | 1.000 |
| **sig.** | 0.014 | 0.445 | 0.000 | 0.839 | 0.257 | 0.035 | 0.070 | 0.445 | 0.376 | 0.862 | 0.032 | 0.121 | 0.006 | 0.001 | 0.004 |  |

\*\*significant at the 0.01 level (2-tailed), \*significant at the 0.05 level (2-tailed)

TABLE 1.  Kendall’s Tau Correlations between the Attributes of Learners’ Learning Behaviours

The best strategy to use when a learner experiences failures in completing certain levels and wants to increase the number of completed levels is through Theoretical Resolution (THR)—return to the theoretical explanation provided in Level 1. This strategy has the most significant positive near moderate correlation to Completeness (CMP) compared to other After-Failure Strategies. Other strategies, Repetitious Resolution (RPR) and Retreating Resolution (RTR) can also be used since they have significant positive correlations with Completeness (CMP), despite their strengths are weaker than Theoretical Resolution (THR).



Fig. 3. Summary of the correlations between the variables of learning behaviours and learning outcomes after learning using Sort Attack.

Similar to Completeness (CMP), attributes that correlate significantly with Completeness also correlate significantly with Number of Completions (NCO), except that their correlations’ strengths to the Number of Completions are slightly stronger than their correlations to Completeness (excluding Success Rate (SUR) attribute that is slightly weaker). Therefore, Theoretical Effort (THE), Demonstrative Effort (DEE), Playtime (PLT), Number of Attempts (NAT), Theoretical Resolution (THR), Repetitious Resolution (RPR), and Retreating Resolution (RTR) contribute stronger, positively and significantly, to the prediction of Number of Completions (NCO) rather than to the prediction of Completeness (CMP).

We also found that Error Rate (ERR) does not correlate significantly with Number of Completions (NCO) and Completeness (CMP). It means that having a change in Number of Completions (NCO) or Completeness (CMP) does not predict a change in the Error Rate. The explanation here is that there are two possibilities when a learner completes a level; whether the learner can finish the level by making one or more mistakes or without making any mistake at all. The likelihood of these possibilities to occur are of equal chances. When the player moves to a higher level, the person is introduced to new difficulties that increases the possibility of making many mistakes, but the person will increase the possibility of completing the level after playing several times and thus reducing the mistakes made. This explanation is also supported by the insignificant close-to-zero correlations that Error Rate has with Number of Completions and Completeness. Furthermore, Error Rate (ERR) can be significantly predicted by Number of Game-Overs (NGO) (0.680\*\*) and Number or Errors (NER) (0.536\*\*). An increase in one of both Number of Game-Overs (NGO) and Number or Errors (NER) positively and strongly predicts an increase in the Error Rate (ERR). The summary of our findings is shown in Fig. 3. The figure shows the simplified relationships between the variables (it only displays relevant variables).

# Conclusions

Based on the findings in the context of our research, we conclude that to have a higher rate of completing a level, we can increase the number of the completed levels and the frequency of the levels completed. To increase them, learners need to dedicate their efforts to understanding the algorithms theoretically, pay attention to the demos or illustrations, spend more time playing, and exert more attempts to complete the levels, with the latter having the strongest magnitude in predicting the frequency of level completions and completing all the levels.

When learners make mistakes or experience failures, the best way to overcome the problems is by returning to review the theoretical explanation. It is a type of didactic learning [29] in which one tries to learn certain topics through the explanation that have been provided by others. This method, in certain situations, is efficient since we do not have to build the knowledge from scratch through iterative experimentation as implied by pure constructivism [30] and pure experiential learning [31]. Other two constructivism-like approaches, repetitively retry a level and learning from previous levels exerting trial-and-error approach [32] or associative learning [33] can also be applied. It is imperative to note that their effects are not as strong as the effect of learning from the theoretical explanation.

Additionally, experiencing failures does not always mean a bad thing since making mistakes is always a part of a learning process. The number of errors we made correlates positively, moderately, and significantly with the number of efforts we put forth when we learn something new. In the end, constant and repetitive efforts to learn something new will lead us to success.

Therefore, for design implications, we need to design games that allow learners to make mistakes, retry, and repetitively learn from their previous failures until they are proficient enough to generate successes in their learning. The design also focuses on the need to allow the learners to learn from the previous levels. Learners may experience this levels to be easier than the difficult ones. This helps in the way we build our capability by learning from the slightly easier challenge to tackle a more challenging one. Most games nowadays already accommodated these kinds of design. They do allow many retries, so players can learn from failures. However, the findings about the after-failure strategies can certainly help in designing stronger Serious Games. For an example, the design needs to provide some theoretical explanation in which learners can revisit after experiencing failures. In this way, they can develop their understanding didactically through the explanation already provided by the tutors.

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