International Journal of Game-Based Learning
Volume 12 • Issue 1

Gamification of Computer Programming Tasks to Promote the Growth Mind-Set in a Disadvantaged School

Garry Gorman, Letterkenny Institute of Technology, Ireland
Nigel McKelvey, Letterkenny Institute of Technology, Ireland*
Thomas Dowling, Letterkenny Institute of Technology, Ireland

ABSTRACT

This paper describes a growth mindset intervention with junior cycle coding students in a disadvantaged school in Ireland. This intervention builds on the work of O'Rourke et al. and applies findings to a computer programming setting where gamification is used to incentivise growth mind-set behaviour in students learning to code. Data revealed a large drop in the perseverance of effort with the control group while learning computer programming. Significantly, the intervention shielded the focus group from experiencing the same drop while learning to code. This research found an increase in the growth mindset behaviour as the intervention progressed. Additionally, the study revealed that some game elements were effective at incentivising growth mindset behaviour like perseverance, while others were less successful. These findings are important for educators to consider when they find their coding students showing a helpless response to challenge as this research sets out a clear path to successfully incentivise persistence and changing strategy in the face of challenge.

KEYWORDS

Blockly, Gamification, Grit, Growth Mindset, Programing, Tenacity

1. INTRODUCTION

Resilience has been identified as a necessary character trait with students studying Coding in the new Junior Cycle (Fleming & McInerney, 2019). Many teachers have reported timetabling as the most significant challenge to the successful rollout of Coding in second level schools. These teachers have described the nature of Junior Cycle short courses as having led to Coding being made compulsory in schools in order to fit it into the timetable leading to many students disengaging from the subject due to lack of choice (Fleming & McInerney, 2019).

Research has shown that students from a low socioeconomic background are more likely to disengage from Computer Science (CS) education than their wealthier peers due to a lack of social connection with the subject and having no family history of employment in the tech industry (Parker et al., 2018, Ryoo, 2019). A recent study presents that low socioeconomic background is a significant barrier to academic success (Program for International Student Assessment [PISA], 2018). However,

DOI: 10.4018/IJGBL.287827 *Corresponding Author

mind-set interventions have been shown to improve performance, particularly in disadvantaged and low performing students (Cutts et al., 2010, Quille & Bergin, 2020).

There are many studies with varying degrees of success where an intervention is developed to improve mind-set with CS students (Quille & Bergin, 2020, Park et al., 2017). Gamification has been successfully used as a method to incentivise growth mind-set behaviour in mathematics students (O'Rourke et al., 2016).

It is the purpose of this paper to ascertain if the gamification of computer programming tasks can improve the mind-set of Junior Cycle Coding students in a disadvantaged school, and hence, incentivise growth mind-set behaviour.

In order to analyse how players interact with the game, the results are examined through the lens of Bartles Taxonomy of Player Types (Johnson, 2016). There are four player-types, Killers, Achievers, Socialisers and Explorers. Bartle (1996) classifies player styles in an attempt to predict player preferences. Achievers enjoy being rewarded for their efforts and are goal orientated. Explorers are process oriented, are curious and play by trial and error in the pursuit of discovery. Socialisers play the game to form relationships with other players. Killers play to dominate other players and are motivated by competition (Burmester 2020). Bartles Taxonomy will provide a clear image of how the game performs as a growth mind-set intervention and help explain how each game element performs in influencing the mind-set of the participants.

2. LITERATURE REVIEW

Dweck (2017) argued that there are two different types of mind-set, the growth mind-set and the fixed mind-set. A fixed mind-set person believes that their qualities are set in stone and feels the need to prove their abilities repeatedly. Students with a fixed mind-set believe that their intelligence and qualities are a fixed entity, and it becomes important to them to prove to themselves and to others that they have these qualities. Students with a fixed mind-set will go to great lengths to appear competent or successful even going as far as cheating (Ehrlinger et al., 2016). In contrast, when a student believes that their intelligence and ability can grow and develop through effort, persistence and hard work, this is the growth mind-set (Dweck, 2017). When learning computer programming, growth mind-set students are more likely to show a mastery response to challenge, to take a risk and to view mistakes as part of the learning process (Murphy & Thomas, 2008; Kizilcec & Goldfarb, 2019). Students with a growth mind-set respond best to learning goals, set goals for themselves and stick to them in the event of a setback (Dweck, 2016). These students are determined to become smarter, stronger and get better and their thoughts and actions are led by this desire (Dweck, 2016). All in all, holding a growth mind-set leads to higher performance, motivation and perseverance inside and outside the classroom (Dweck, 2016).

Dweck (2017) described a person with a growth mind-set as believing that their true potential is unknown, that it is impossible to foresee what can be accomplished with years of passion, toil and training. She continued stating that believing that one's ability can be cultivated creates a passion for learning, a desire to overcome deficiencies and seek challenges that stretch. Dweck (2017) concluded that holding a growth mind-set is to have a passion for stretching one's self and sticking to it, especially when things are not going well, allowing one to thrive at the most challenging times.

Studies have shown that a growth mind-set can be developed (Limeri et al., 2020; Yeager, 2019). Mueller & Dweck (1998) conducted a study to determine the effect that praising children for their character rather than their intelligence would have on subsequent tasks. In their study, the children completed a simple task and receive feedback on their work. The children were divided into 3 groups. The first group received feedback praising their intelligence, while the second group were praised for their effort. The third group were simply praised for their scores. Mueller & Dweck (1998) found that the group that were praised for effort outperformed the other groups. These children also preferred to work on more difficult tasks where there was a learning opportunity. Dweck (2017) expanded on this study arguing that effective growth mind-set based feedback can lead children down the path of hard work and greater hardiness while motivating people to choose challenging tasks and confront their mistakes. Dweck (2017) described this feedback as rewarding people for taking initiative, seeing a challenging task to conclusion, for struggling to learn something new, for being open to and acting on criticism while showing resilience in the face of setbacks.

Research would suggest that there is a potential gap in knowledge on mind-set interventions when students are studying Junior Cycle Coding. Cutts et al., (2010) conducted a study in a Higher Education where students studying introductory computer science received a growth mind-set intervention involving three separate strategies: the teachers directly taught growth mind-set concepts to students at the beginning of class; growth mind-set messages were printed on the top of feedback reports on assignments; and students were given a crib-sheet containing problem solving strategies to help when they got stuck. They found that the combination of the direct teaching of mind-set theory and applying growth mind-set feedback messages on returned work lead to a significant change in mind-set, and a significant improvement in attainment. Cutts et al., (2010) concluded that teaching mind-set alone did not transfer to improvements in test scores. This is because students come up against failures regularly and the mind-set message needs to be repeatedly reinforced. They also concluded that teaching CS without any focus on mind-set reinforces a fixed mind-set due to the frequency in which CS students encounter failure.

In contrast, Burnette et al., (2019) implemented a growth mind-set study involving a large-scale online intervention on CS students. They found that while there was a significant improvement in levels of interest toward CS following their intervention, there was no effect from their growth mind-set intervention on their final grades compared to the control group.

Similarly, Simon et al., (2008) conducted a study where a "saying is believing" intervention was attempted to foster a growth mind-set in CS students. This intervention involved only a single lecture and a one-page reminder and reported no significant benefit to the students involved. This suggests that a single lecture may not be as effective as integrating the growth mind-set intervention into daily lessons.

Yeager et al., (2016) found that when students have a fixed mind-set as a result of economic disadvantage, this can reduce the impact of a growth mind-set intervention on academic achievement. However, Claro et al., (2016) conducted a study in Chile where a growth mind-set intervention was conducted in multiple schools across all socioeconomic backgrounds. They found that lower-income families are twice as likely to hold a fixed mind-set than their wealthier peers. They also found that when lower-income students hold a growth mind-set, they are buffered from the negative effects of poverty on academic achievement. Claro et al., (2016) concluded that mind-set is a more important predictor of success for lower-income students than their wealthier peers and that a fixed mind-set is more debilitating when students have had to overcome significant barriers to succeed.

Educational disadvantage can have a significant impact in the CS classroom. Students that come from cultures that have no history in the CS industry can develop preconceived notions that a career in CS is for other people. The lack of ethnic, racial and gender diversity in the CS workforce is not as a result of a lack of ability or interest (Pinkard et al., 2017). A study by Ryoo (2019) investigated the efficacy of pedagogies with second level students in disadvantaged schools studying CS on a compulsory basis. Most participants were from a low socioeconomic background. Students asked, "What's the point of learning this?" and "Why do we need to know this?" as they struggled to make a connection with CS outside of school. She found that these students could not relate to CS as an area of interest as there was no history of CS employment in their cultural background.

Quille and Bergin (2020) replicated the growth mind-set intervention that Cutts et al., (2010) previously implemented on CS1 students. They found that the average attainment of the focus group, compared to the control group, increased by almost 10%, but more significantly, the pass rate increased by 28%. Furthermore, Quille and Bergin (2020) found that the growth mind-set intervention has a larger effect on low and middle performing students, while having a negligible effect on high performers.

Dweck and Yeager (2019) concur arguing that growth mind-set interventions effect some sub-cohorts more than others, that lower achieving students reported the most positive results.

Research by Flannigan et al., (2016) measured the mind-set of CS students as they progressed through CS1. In this study, no intervention took place. They found that the participants showed a significant increase in the fixed mind-set and a reduction in the growth mind-set suggesting that studying CS fosters a fixed mind-set.

Digital game-based learning is an effective way to teach introductory computer programming constructs (von Davier, 2019). Blockly Games: Maze and Classic Maze from code.org are examples of digital games that use block-based programming to introduce computer programming principles.

A study by O'Rourke et al., (2014, 2016) where a growth mind-set incentive structure was used in an online digital game to reward players for changing strategy, perseverance and incremental progress found that low performing students played the game for longer, changed strategy more often and were more likely to persevere on challenging levels. However, this study only effected the players' perseverance by a matter of seconds. Plass et al., (2015) argue that gamification is an effective way to engage learners on an emotional level, but in order to maximize engagement, digital games must stimulate situational interest through enjoyable game mechanics and provide scaffolding to the learner in the form of hints or feedback.

The literature has shown that growth mind-set interventions in CS have had mixed results. This may be because they compare mind-set to academic achievement over a short period of time. It is the intention of this research to measure the impact that the intervention has on growth mind-set behaviour throughout the intervention to determine the efficacy of the intervention at different stages.

2.1 Theoretical Perspective

Plass et al., (2015) argue that a typical digital game rewards success occasionally and that good games are neither too easy nor too hard. If a game is too easy the player will become bored and quit, while if the game is too difficult, the player will become frustrated and quit. Good games are designed so that the player can succeed, but only with some struggle. Good games are aimed to be within Vygotsky's (1978) Zone of Proximal Development (ZPD).

When describing the ZDP, Vygotsky (1978) argued that a child develops between two levels. The lower level is what a child can do on their own while the upper level is what the same child can accomplish with the help of a More Knowledgeable Other (MKO). The ZPD is the gap between these two levels. As the child develops and learns, the upper ceiling of the ZPD rises resulting in the child becoming capable of more.

Vygotsky (1978) argued that when a child is at play, he/she "is always above his daily behaviour, in play it is as though he were a head taller than himself ". McLoud (2020) asserted that a child can operate at the upper limit of their ZPD while engaged in play, that they can regulate their behaviour beyond their current ability in order to follow the rules of the game. Plass et al., (2015) argue that good educational games aim to be within the player's ZPD.

Bodrova, Germeroth and Leong (2013) state that in play, it becomes possible that a child can adopt a set of rules they need to follow in order to play the game. Play becomes the first activity where a child must self-regulate their behaviour to follow the rules of the game, denying their desire for instant gratification, supressing their immediate impulses. Vygotsky (1967) observed that in play "at every step the child is faced with a conflict between the rule of the game and what he would do if he could suddenly act spontaneously. In the game, he acts counter to what he wants . . . [achieving] the maximum display of willpower" (Vygotsky 1967). This suggests that the child can set aside their desire to act spontaneously, that they can choose to demonstrate growth mind-set behaviours when the rules of the game demand it (Vygotsky 1967).

Vygotsky's theory of social constructivism places the adult, child or, in the case of this research, a video game MKO as highly important in the role as guide through the ZPD. The ZPD relates to the difference between what a student can already do on their own and what they can achieve with the assistance of someone with more knowledge or skill. For example, if a student attempts to solve a problem with code, he/she may struggle to the point of giving up, but may be able to solve the problem with the assistance of an MKO and develop the ability to solve future problems using the strategy learned from the MKO (Woolfolk 2004).

Vygotsky (1978) viewed the ZPD as the space where the student will develop the skills and knowledge that they will eventually use on their own while developing higher mental functions. Vygotsky argued that interaction between the student and the MKO (video game) is an effective method of developing knowledge and skills (McLeod 2020).

Massive Open Online Courses (MOOCs) are a well-established form of MKO for learning. This technology faces a significant challenge to retain students until course completion, with only a small percentage of students completing the courses they begin and little research available into how to engage students in an online learning environment (Jordan 2015). However, video games are known for their motivational ability, influencing players to perform difficult tasks for extended periods of time (O'Rourke et al 2016). Plass et al., (2015) argue that games-based learning is the answer engaging students to persist in learning activities that they would otherwise find boring. They define games-based learning as a balance between the need to cover subject matter with the desire to prioritise game play. To further incentivise a learning activity, gamification may be used to incentivise and motivate players to engage in a task that they would otherwise find unattractive (Plass et al., 2015). This suggests that redesigning MOOCs to include rewards for performing tasks under certain rules would make these activities more interesting and engaging.

Plass et al., (2014) produced a framework for games-based learning. As part of this framework, they outline the function of digital games for learning demonstrating how to use games as an MKO within the ZPD. Plass et al., (2014) describe the roll of educational video games as follows:

- To introduce new knowledge and skills as part of game play;
- To provide opportunities to practice existing knowledge or skills in order to automate them;
- To provide opportunities for teamwork, problem solving, creativity etc.

2.2 Research Question

To what extent does an intervention using the gamification of computer programming tasks improve the grit and growth mind-set in disadvantaged students studying Junior Cycle Coding?

3. DESIGN AND METHODOLOGY

During the school year 2020-2021, two first year classes in a DIES school participated in this study with a total of 21 participants aged between 12 and 13. The focus group contained 12 students while the control group had 9. The school at the centre of this research already had two distinct class groups studying Coding in first year, therefore it was decided to continue with the existing groups in order to maximise the integrity of the data collected by ensuring the students felt that the intervention was taking place as part of their normal lessons.

Data was collected using two surveys, the Grit Survey and the Implicit Theories of Intelligence Questionnaire(ITIQ). The students were surveyed again at the end of the intervention to determine the impact of the intervention on their grit and mind-set.

The two groups were compared before the intervention commenced to determine if any differences existed between the groups that may have an effect on the intervention. The initial grit and ITIQ scores were analysed using a t-test to determine if there was a statistically significant difference between them prior to the study. The results in Table 1 show the mean scores for each group and the p-value demonstrating that no statistically significant difference existed between the two groups.

Table 1. p-values pre-intervention

	Focus	Control	p-Value
Mind-set	3.96	4.06	0.77
Grit	3.11	3.08	0.87

The two groups involved in the study had a similar spread of girls and boys with both groups containing 33% girls and 67% boys. The two groups had a slight difference in the nationalities of the students with 75% of the focus group coming from Ireland while 67% of the control group being Irish. However, all students involved in this study spoke English very well and it was not expected that language levels would be a potential barrier to success. All students involved in this study are from a low socioeconomic area.

The intervention was divided into two distinct sections. The first element of the study involved participants playing a game designed to teach Coding that had an incentive structure designed to reward growth mind-set behaviour. The second element involved the direct teaching of the growth mind-set.

The study took place over a one-month period where the participants followed their normal Coding lessons which involved two 40 minute lessons per week. In addition, the focus group received a 40-minute lesson once a week where the fundamentals of the growth mind-set were taught. The growth mind-set lessons consisted of videos from well-known celebrities and testimonials from previous students who had initially struggled but succeeded through persistence, use of strategy in the face of challenge and risk-taking. Additionally, the focus group played the video game, designed to incentivise growth mind-set behaviour, for the final 10 minutes of each Coding lesson. The control group followed their Coding lessons as normal without any intervention.

To explore the effects of teaching Coding through a digital game that incentivised growth mind-set behaviours, a game was created that used block-based coding to control a car. The game, Maze City, contained an incentive structure that awarded points for growth mind-set behaviours, such as, persistence, risk taking and use of strategy. These behaviours were selected based on Dweck (2017) to reward actions such as completing a task, responding to feedback, taking risks, showing persistence and changing strategy in the face of challenge.

3.1 Maze City

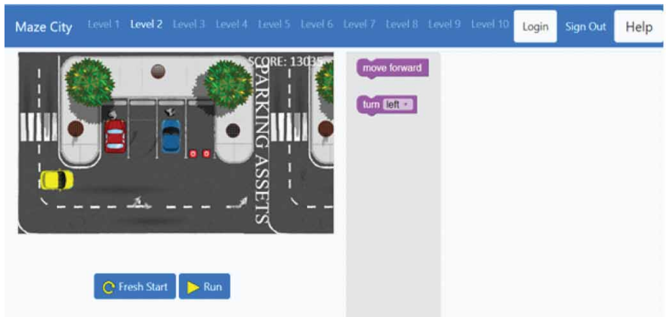
The game was designed and developed by the researcher to teach introductory coding constructs to first year Junior Cycle students. The game was designed to support conceptual understanding of sequencing and loops. To play, the student navigates a car along a road towards a finish line avoiding obstacles and collecting coins on route. The player uses block-based programming to control the car by dragging blocks from a toolbox and dropping them in the workspace, snapping them together in sequence and then clicking the run button to execute the code. Figure 1 shows the second level of Maze City where the player directs the car into a parking space using the blocks available in the toolbox.

The purpose of the game is to award points for growth mind-set behaviours and to measure these actions as the intervention develops to determine if these rewards will modify student behaviour so that they increase in frequency and improve grit and mind-set reflected in the post surveys.

The following growth mind-set behaviours, as described by Dweck (2016, 2017), were used to guide the design of Maze City:

- Risk taking that leads to a learning opportunity
- Persistence of effort
- Seeing a task through to completion
- Changing strategy in the face of challenge

Figure 1. Maze City Level 2



- Responding to learning goals
- Exploration and experimentation
- Mastery response to challenge

3.2 Incentive Structure

Maze City has a points-based incentive structure designed to reward growth mind-set behaviour. The incentive structure created by O'Rourke et al., (2014, 2016) rewarded effort, use of strategy and incremental progress. These same growth mind-set behaviours were rewarded in this research. These types of behaviours support learning objectives rather than learning outcomes or performance goals which, when combined with growth mind-set praise, have been shown to promote a growth mind-set (Dweck, 2017).

Through the lens of Bartles Taxonomy, Maze City was designed to incentivise Achievers to experiment with new code block and respond to failure by changing strategy while maintaining their work ethic. Zenn (2017) described Explorers as players who enjoy making new discoveries, unlocking new functions in a game. Burmester (2020) declared that Explorers respond positively to failure, learning from errors and avoiding making the same mistakes in the future. In contrast, Burmester (2020) argued that Achievers are highly motivated by gamification and are keen to progress through game levels at a fast rate taking the direct path to success. Achievers are intrinsically motivated to score the highest points at the expense of all else, including exploring, and are willing to work hard to get there (Zenn 2017).

However, the game was not designed with Socialisers and Killers in mind. Maze City game is single-player with no chat function. There is no opportunity for one player to dominate another built into the game and there is no function for players to interact with each other.

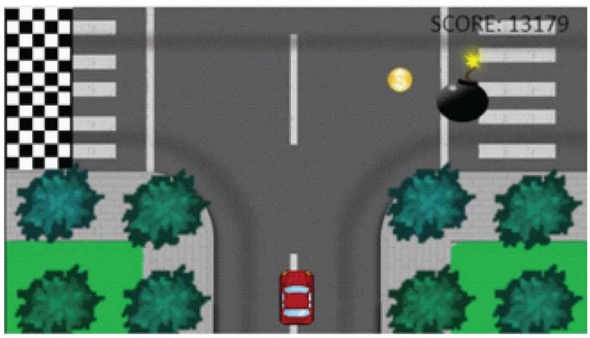
Figure 2 shows the growth mind-set scoreboard which is displayed on screen at all times. The scoreboard registers all scores as they happen drawing attention towards the growth mind-set behaviour that students are being rewarded for. The combination of the following six metrics capture growth mind-set behaviours and determine the overall score for each player.

3.2.1 Risk Taking

People with a growth mind-set have a comfort with taking risks or choosing a task that is at or above the upper limit of their ZPD (Dweck, 2017). In Maze City, to incentivise risk taking, points are awarded for collecting coins located close to danger. By setting tasks in this way, it is envisaged that students will develop a positive attitude towards challenging work, as they are rewarded with points even if they have yet to solve the level. The collection of coins is used in levels one, three, five, six and ten to motivate and incentivise the player to take risks and accept challenging tasks as learning opportunities when an easier solution is available (Dweck 2017). Figure 3 shows a coin which is

Figure 2. Growth Mind-set Scoreboard

Figure 3. Level 3, Coin Collection



located off the easiest path to the finish line and close to a bomb. By combining the points awarded for the collecting the coins with the increased situational interest of danger, it was envisaged that students will become more intrinsically and extrinsically motivated and therefore exhibit risk taking behaviours and challenge acceptance.

From a Bartle's Taxonomy perspective, the *Risk Taking* game element uses points to motivate the Achiever to experiment with code to collect the highly incentivised coin. The large incentive is designed to encourage the Achiever risk failure in pursuit of reward. It was envisaged that the Explorer would exhibit little fear of failure and attempt to collect coins out of curiosity regardless of the incentive structure.

3.2.2 Mastery Response to Challenge

Murphy and Thomas (2008) and Kizilcec and Goldfarb (2019) argued that CS students with a growth mind-set exhibit a mastery response in the face of difficulty and view failure as an opportunity to learn. To incentivise a mastery response to challenge, *Changing Strategy* points are awarded for using the help button which offers a digital MKO in the form of a help modal. It is envisaged that when students are rewarded for seeking help in the face of difficulty, that they will try a new approach based on guidance from the help modal and will be less likely to exhibit fixed mind-set behaviours, such as, quitting, complaining or blaming external factors (Slack, 2020).

Through the lens of Bartles Taxonomy, the Explorers will naturally tend towards investigating all game functions including the help button. However, the Achievers are expected to react positively to the help button but only after they realise that it is incentivised.

3.2.3 Persistence of Effort

The persistence metric is a product of time. The player is awarded *Working Hard* points every ten seconds that they are engaged in the game. This reward is designed to incentivise staying on task. It was envisaged that students will be encouraged to continue playing the game by the combination of playful learning and see their score increasing with the passing of time, motivating the player to stay on task for longer.

Burmester (2020) argued that the Achiever is likely to lose interest in a game quicker than other player types, especially if they feel they are not winning. The *Working Hard* points are designed with the Achievers in mind drawing attention to the fact that persistence is rewarded and that staying on task is a form of winning.

3.2.4 Seeing a Task Through to Completion

The player is rewarded with points on the growth mind-set scoreboard as they solve each level. This productive struggle metric captures when the player has successfully completed a level. *Coding Effort* points are awarded here to incentivise completing the task at hand and to avoid rewarding effort that does not lead to a successful outcome (Dweck 2017).

Achievers are naturally driven by their desire to progress through the levels (Burmester 2020). The combination of this desire and the awarding of points for level completion is designed to motivate and engage Achievers.

3.2.5 Starting Again in the Face of Challenge

In order to foster a positive relationship with failure, the consequences of failure must be minimal to encourage risk taking, trying new ideas and exploration (Plass et al., 2014; Dweck 2019). In order to convey the message that failure is not permanent and is part of the learning process the player has an infinite amount of turns to be successful and there is no “game over” condition. When the player sends the car in the wrong direction or on a collision course with an obstacle, the player can simply click the *Fresh Start* button to returned the car to the starting position where the they can modify their code and try again without consequences.

Plass et al., (2014; 2015) argued that when graceful failure is adopted into educational games, the player has the opportunity to set and change strategy towards achieving their learning goals. In order to allow and reinforce the message that failure is an expected part of learning, points are awarded when the *Fresh Start* button is clicked to reward the player for starting again from a fresh perspective. This allows the learner to explore the functions of new blocks of code and to experiment without fear of a negative outcome.

From a Bartles Taxonomy perspective, Explorers are anticipated to experiment with this game element from the very beginning. The *Fresh Start* button will facilitate their instinctive tendency to discover the road less travelled (Burmester 2020). In contrast, the Achiever is expected to be less engaged by this game element as they are more interested in quick progress via the direct route to goal. The points awarded for using the *Fresh Start* button are aimed at the Achiever in the hope that they will be motivated to change strategy in the face of challenge by the fact that the act is incentivised.

3.2.6 Exploration and Experimentation

In order to further encourage changing strategy in the face of challenge, *New Ideas* points are awarded to incentivise the player to experiment with the new blocks as they appear. This metric is triggered when the player executes code containing a new block of code. By awarding points for experimenting with new blocks, it was envisaged that players would be incentivised to explore the functions of new blocks as they appear, leading to new learning. Combined with graceful failure, *New Ideas* points were designed to change the player's attitude to failure so that failure would be viewed as a necessary part of the learning process (Dweck, (2016).

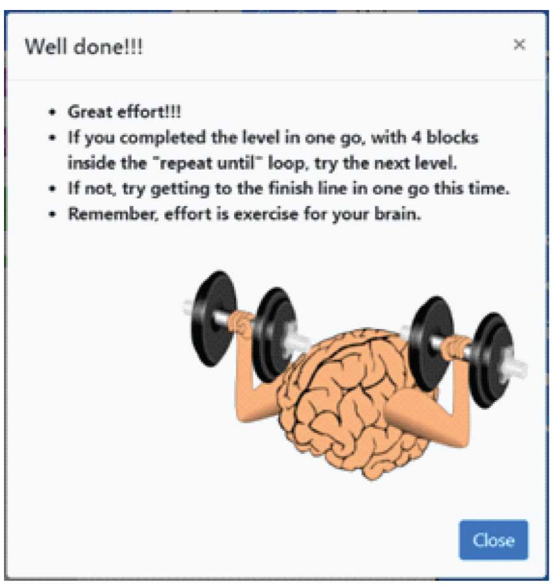
Through the lens of Bartle's Taxonomy, the *New Ideas* element of the game is designed so that Explorers get credit for their instinctive motivation to make new discoveries (Zenn 2017). Explorers will enjoy experimenting with new blocks regardless of the incentive structure. In contrast, Achievers will be less inclined to experiment with new blocks and are expected to be motivated to explore their functions by the points awarded for their use.

3.3 Help Modal and Level Complete Modal

Cutts et al., (2010) argued that CS students holding a fixed mind-set can demonstrate a helpless response in the face of challenge. To reduce the likelihood of a helpless response to failure in this game, a help button, located in the navigation bar, provides an opportunity for students to change strategy in the face of challenge, offering scaffolding by acting as an MKO by giving the learner a clear guide on how to play the game without solving the puzzle for them. The help modal provides a guide on how to use Blockly to control the car, how to run the code and how to start again using the fresh start button. The help modals contain a video guide to suit the visual learner and for non-English speaking students. The modals also contain text to suit the verbal learner. The help modal is designed to reduce the cognitive load when the fixed mind-set student is close to quitting.

The Murphy and Thomas (2008) study concluded that CS students should be praised for effort rather than ability in order to foster a growth mind-set. Although, Dweck (2017) argued that praising effort that has not led to a successful outcome can be counterproductive. In order to praise students for their effective effort, the player receives growth mind-set feedback, such as, "great effort" or "hard work leads to success", but only when the car crosses the finish line. Figure 4 shows the modal that appears and praises the player in a growth mind-set way and sets a challenge to improve on their previous work. The player is challenged to attempt the level using less code and to risk collecting a coin placed close to danger that requires a more complex solution than already attempted, while also reinforcing the growth mind-set message.

Figure 4. Level Complete Modal



The nature of the Explorer will be motivated to go back and discover the technicalities of game elements that they may have missed in a quest to learn how to take advantage of them in future levels (Zenn 2017). In contrast, the Achiever is naturally motivated by progressing through the levels and the idea of repeating levels will be less appealing (Burmester 2020). For this reason, all the points available through the incentive structure remain in place when a player repeats a level to encourage the Achievers to revisit levels and build up their scores.

To avoid the possibility that the player might game the system by simply clicking the help button and fresh start buttons continuously to gain points, two fail-safes were implemented to minimise this risk and to prevent this from happening. The points awarded for clicking the fresh start button were reduced every time the player clicks the button minimising the incentive to use it to game the system. To gain the points from the help modals, the player must view each modal and click the exit button on the last modal.

3.4 Levels

The game has ten distinct levels, each designed to gradually move the player through their ZPD introducing new coding constructs while rewarding growth mind-set behaviours. Each level has its own learning objectives stated in the bottom left to focus the learner on what is to be learned. To familiarise the player with Blockly, level one is kept simple with a single block of code in the toolbox that must be used three times to complete the level. The car must travel from its starting position to the finish line in a straight line. In level one, the learner becomes familiar with sequencing, that the code is executed from top to bottom and that points are awarded for growth mind-set behaviours.

Level two introduces the turn left/right block as the learner must navigate the car into a parking space. The cognitive load is increased as the learner must use the new block to solve the puzzle. In this level, it becomes possible that the player will guide the car off course. Here, the player is introduced to the fresh start button and is shown a video in the help modal to encourage its use.

In level three the coin is reintroduced to incentivise choosing a difficult task that contains an element of risk as a learning oppertunity. A coin is placed slightly off course, close to a bomb.

The subsequent levels increase in difficulty raising the upper ceiling of the ZPD requiring more complex code to solve the puzzles. Furthermore, repeat blocks are introduced and the students are incentivised to experiment with them with points from the *New Ideas* element of the scoreboard.

4. ANALYSIS OF RESULTS

This section discusses the results from the Grit Scale, the ITIQ and the growth mind-set scoreboard. The before and after survey scores are analysed and compared to the growth mind-set scoreboard results to determine the effectiveness of each of the game element. Firstly, the ITIQ results are examined to determine if the intervention positively promoted a growth mind-set. Secondly, the Grit Scale results are analysed to discover the impact that the intervention had on perseverance and consistency of interest. Thirdly, the growth mind-set scoreboard results are examined to determine the impact that each game element had on student behaviour. Finally, the results are analysed through the lens of Bartle's Taxonomy to examine the effect that player-types had on participant behaviour and mind-set.

In order to analyse the data presented in this study, t-tests were used to determine the statistical significance of the findings. Furthermore, to measure the effect size that the intervention had on the focus group relative to the control group, a Cohen's d was conducted, as presented by Ferguson (2016).

4.1 Mind-Set Analysis

The focus group saw an overall slight increase in mind-set scores from pre to post intervention. The mind-set scores were taken from Implicit Theories of Intelligence Questionnaire (ITIQ) as presented by DeCastella and Byrne (2015) with values ranging from 1 to 6. Table 2 shows that a score above 4.4 results in a strong growth mind-set while a score below 2.1 demonstrates a strong fixed mind-set.

Table 2. Mind-set Values

Mind-Set	Survey Value
Strong Growth Mind-Set(G)	4.5-6
Growth Mind-Set with some Fixed ideas(G-F)	3.3-4.4
Fixed Mind-Set with some Growth ideas(F-G)	2.1-3.2
Strong Fixed Mind-Set(F)	1-2

A score between 3.3 and 4.4 is considered a growth mind-set with some fixed ideas, while a score between 3.3 and 4.4 shows a fixed mind-set with some growth ideas.

Table 3 shows that the average mind-set in the focus group increased by 3% from 3.96 to 4.06 while the control group average fell by 3% from 3.83 to 3.71. The data shows that the gamification of computer programming tasks improved the growth mind-set of the students by a small amount. However, a t-test was conducted to determine the statistical significance of these findings. This analysis returned a p-value of 0.47 which suggests that the gains achieved by the focus group over the control group are not statistically significant.

4.2 Grit Analysis

Again, the focus group saw an overall small increase in grit scores as a result of the intervention. The grit scores were calculated as per Duckworth and Quinn (2009) with values ranging from five (extremely gritty), to one (not gritty at all). Both groups scored similarly in pre-tests, but the post-tests results tell a very different story. Figure 5 shows that the control group saw a 20% decrease in overall grit with a 36% drop in perseverance of effort. In keeping with Ryoo (2019), this demonstrates that the intervention was effective at buffering the negative effects that learning to code can have on perseverance of effort.

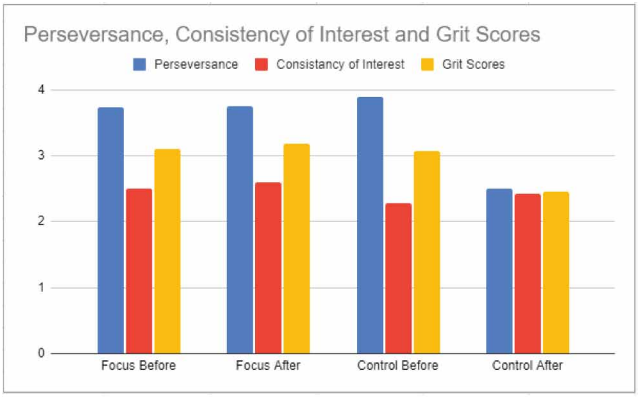
Again, a t-test was conducted and returned a p-value of 0.05 which shows that the overall comparison between grit scores of the focus group to the control group are reliable and statistically significant. Furthermore, the Cohen's d was calculated to measure the magnitude that the intervention had on the grit of the focus group relative to the to the control group. This calculation returned a delta of 0.31, confirming that the intervention increased the grit of the focus group relative to the control group by a small yet statistically significant amount.

Figure 5 shows that the perseverance of the control group dropped by 36% while the focus group increased by 0.5% over the course of the intervention. Consistent with Flannigan et al., (2016), this suggests that learning CS at Junior Cycle level fosters a fixed mind-set leading to a reduction in perseverance of effort. The t-test on the perseverance data returned a p-value of 0.003 showing that the data is reliable. Furthermore, the Cohen's d returned a delta of 1.47. This demonstrates that the intervention had a large and statistically significant effect on the perseverance of effort on the focus group relative to the control group.

Table 3. Impact of the Intervention on Mind-set

ITIQ Mean	Before	After	Effect
Focus	3.96	4.06	3% increase
Control	3.83	3.71	3% decrease

Figure 5. Perseverance, Consistency of Interest and Grit



4.3 Impact of Game Elements

The game was designed to incentivise growth mind-set behaviours by awarding points for each instance that these actions were exhibited. These scores were collected by the growth mind-set scoreboard and compared to a baseline scoreboard where no extra growth mind-set behaviours were exhibited. This data was used to determine which game elements successfully incentivised growth mind-set behaviour.

Furthermore, many of the questions in the grit survey relate closely to the behaviour that the game elements set out to incentivise. The results from the before and after surveys and the growth mind-set scoreboard were compared to determined which game elements were effective and which were not.

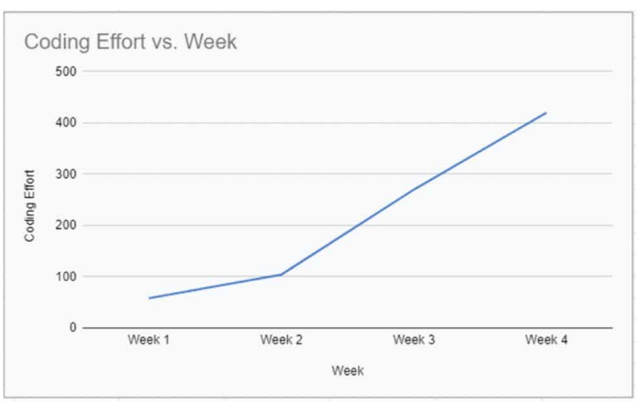
In order to help explain player behaviour, the scores from the growth mind-set scoreboard are analysed through the lens of Bartle's Taxonomy. The scores are examined from the perspective of Achievers and Explorers only as all the game elements were designed to motivate these player-types.

4.3.1 Scoreboard

4.3.1.1 Coding Effort

The students were awarded fifty points when they completed a level to incentivize productive struggle. It was expected that students would maintain their rate of productivity as they progressed into the more advanced levels. However, figure 6 shows that the rate of productivity took a sharp rise in week

Figure 6.



three. This demonstrates that the longer that points were awarded for completing levels, the more levels the students completed. This also shows that awarding points for completing levels in a game designed to teach coding is an effective method of incentivising the growth mind-set behaviour of productive struggle. As established by O'Rourke et al., (2016), awarding points for completing tasks is an effective method of incentivizing productive struggle and has now been shown to be effective applied in a CS setting.

The *Coding Effort* points had an interesting impact on the grit survey responses. Question seven asked "I finish whatever I begin". The focus group answered this question identically in both surveys. In contrast, the control group responded in post-tests with a 42% drop in their perceived productive struggle. This is consistent with the finds of Flannigan et al., (2016) that learning to code promotes a fixed mind-set. However, the focus group were shielded from this effect by the *Coding Effort* element of the incentive structure leading to their perceptions of their productive struggle being maintained.

Through the lens of Bartle's Taxonomy, students who scored high points for *Coding Effort* exhibited strong Achiever characteristics as they were motivated by progression through the levels (Burmester 2020). The student that scored lower in Coding Effort points exhibited Explorer behaviour as they don't care as much about scoring points and are more interested in making discoveries than completing levels (Zenn 2017).

4.3.1.2 Working Hard and Level Complete Modal

Points were awarded for the time students spent engaged with the game and when they completed a level, a model appeared with offering growth mind-set feedback. It was expected that these game elements would maintain engagement in the game while also improving the student's perceptions of themselves as hard workers. The fourth question in the grit scale stated, "I am a hard worker". Again, there was a stark contrast between the focus and control groups pre and post responses. Both groups average scores dropped but the control group dropped by 39% while the focus group reduced by just 11%. This suggests the Working Hard points and the Level Complete Modals were effective at reducing the decline in the participants perceived ability to persevere, although, these game elements were not sufficient to counter the effects that learning to code had on perseverance of effort.

However, the ITIQ scores suggest that the *Working Hard* and *Level Complete Model* were effective at improving the participant's mind-set towards working hard. The fifth question in the survey asks, "With enough time and effort I think I could significantly improve my intelligence level". Again, the control group average scores dropped by 23% while the focus group scores improved by 15%. This suggests that, while this game element may not improve the student's perceptions of themselves as hard workers, they do improve their appreciation for the benefits of perseverance of effort.

From the perspective of Bartle's Taxonomy, it was expected that Achievers would respond positively to the challenges set by the level complete modal and repeat previous levels to accumulate extra points. However, there is no evidence that this was the case as the practice of repeating levels was largely ignored. It is likely that Achievers were more motivated by spending their time rising through the level while continuing to accumulating points (Burmester 2020). In contrast, Explorers may had discovered all that there was to learn from the previous level and scoring extra points was of no interest to them (Zenn 2017).

4.3.1.3 Taking Risks

Dweck (2017) argued that a student with a growth mind-set will choose a difficult task with learning opportunities over a simple task that they are more likely to complete with ease, that the true growth mind-set student will risk failure in the pursuit of learning. Students were rewarded for collecting coins that were placed close to danger when there was no obligation to do so. The fifth question on the grit scale relates to learning goals stating, "I often set goals but later choose to pursue a different one". Both groups again showed a drop in post-test scores with a 24% reduction in the control group and a 13% decline in the focus group. While this suggests that the Risk-Taking points had some impact at reducing the decline in goal setting, this requires a deeper look.

The growth mind-set scoreboard recorded that all students collected a coin in level one, however, only 4 out of 12 participants chose to collect coins in subsequent levels. The coin in level one was placed on the only path to goal while the following coins were all placed in a challenging location. Figure 7 shows a bar chart exhibiting the number of coins that each student collected and their mind-set held prior to the intervention. Figure 7 shows that 3 out of that 4 students held a strong growth mind-set in advance of the intervention. This suggests that coin collection is a good indicator of mind-set but is ineffective in its current form at motivating students that do not hold a growth mind-set to take risks in the pursuit of learning. In keeping with Vygotsky (1978), these students continued to play the game without collecting coins as this game element was not demanded as part of the rules of the game.

Those who collected coins behaved like Achievers as they were aware that there was a substantial reward available for risking collision with an obstacle. It is likely that these Achievers were driven by the incentive structure as they are proud of the status that a high score would give them. In contrast, those who did not collect coins behaved like Explores as they had already collected a coin in level one and had learned that coins brought points to the scoreboard and nothing else. This meant that collecting subsequent coins held no incentive to the Explorer as they are motivated by a sense of wonder. Furthermore, to the Explorer, scoring points is a worthless occupation and having gained the knowledge that coins held no hidden function other than awarding points meant that collecting coins was not attractive (Bartle 1996).

4.3.1.4 Help Button and Changing Strategy

The Help Button and Changing Strategy points were designed to incentivize a mastery response to failure by providing an MKO in the form of a help modal to guide students through their ZPD. In the grit scale, question two states “Setbacks don’t discourage me. I don’t give up easily”. Consistent with Dweck (2017) and Quille and Bergin (2020), the control group took a 27% decline in post-test scores suggesting that the challenges that they faced while learning to code had a negative effect on their perceptions of how well they will face challenges in the future.

However, figure 8 shows that the Help Button had a positive impact on the focus group with an average increase of 5% from pre-tests to post-tests. Furthermore, every student had benefited from the Help Button by the end of the intervention. Table 4 shows the relationship between the points awarded for *Changing Strategy* and the number of students who accessed the help modals. While the initial uptake of help was slow with only one student accessing help in week one and four students by week two, week three saw a major leap in use resulting in all students accessing help as the level of difficulty of the game increased. Furthermore, there is a Person correlation coefficient of 0.98

Figure 7. No. of Coins Collected Mind-Set Prior to Intervention

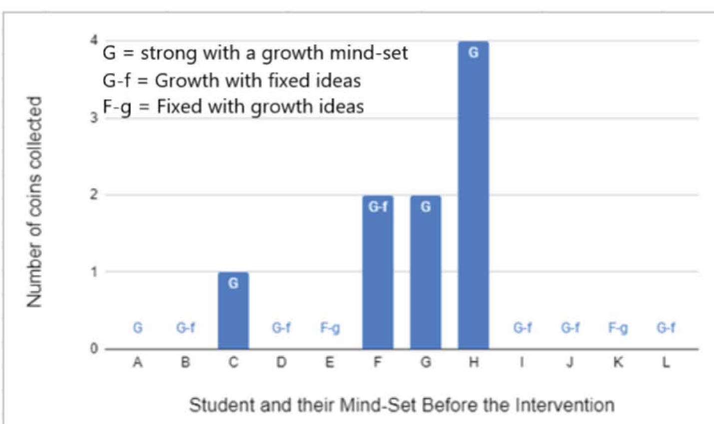


Figure 8. The Effect of the Help Button on Mastery Response

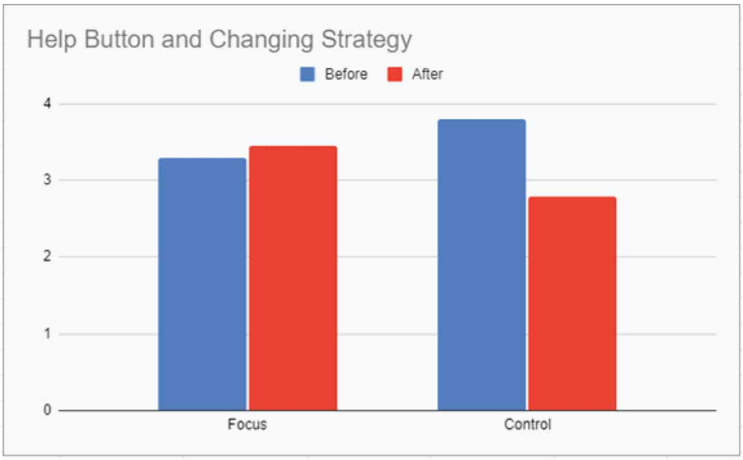


Table 4. Relationship between Changing Strategy Points and the Number of Students Using the Help Modals

	Average Changing Strategy Points	No. of Students Accessing Help Modal
Week 1	2	1
Week 2	29	4
Week 3	60	10
Week 4	87	12

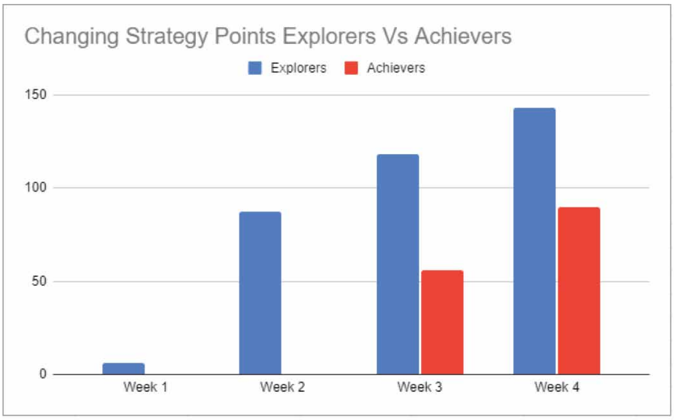
between the two metrics demonstrating that when points are awarded for changing strategy in the face of challenge, all students, regardless of mind-set, benefit from the assistance of a digital MKO. In keeping with Kinnunen and Simon (2011), rewarding students for showing a mastery response in the face of a coding challenge improves their attitude towards difficult work reducing the likelihood of them showing a helpless response to failure.

The students that accessed the help modals in the first two weeks exhibited strong Explorer traits as they set out to discover and understand the technicalities of the game and how to take advantage of them (Zenn 2017). Figure 9 shows that these Explorers continued to make their discoveries through using the help modals consistently throughout the intervention. In contrast, the remaining participants behaved like Achievers towards using the help button. It is likely that Achievers viewed the help button as a delay to their progress through the levels in the first two weeks as Achievers are focused on reaching their goals quickly (Burmester 2020). Furthermore, as the level of difficulty of the game increased and these Achievers began to struggle to complete the more advanced levels, it is likely that Achievers discovered that accessing help was incentivised, therefore worthwhile, and continued to benefit from the digital MKO for the remainder of the study (Zenn 2017).

4.3.1.5 New Ideas

In order to reward experimentation with new blocks, points were awarded when students used new blocks that appeared in the toolbox. It was expected that, as a result of this incentive structure, the students would explore new blocks more frequently as the levels progressed. Their scores were compared to a baseline score that was created by playing the game exhibiting the minimum growth

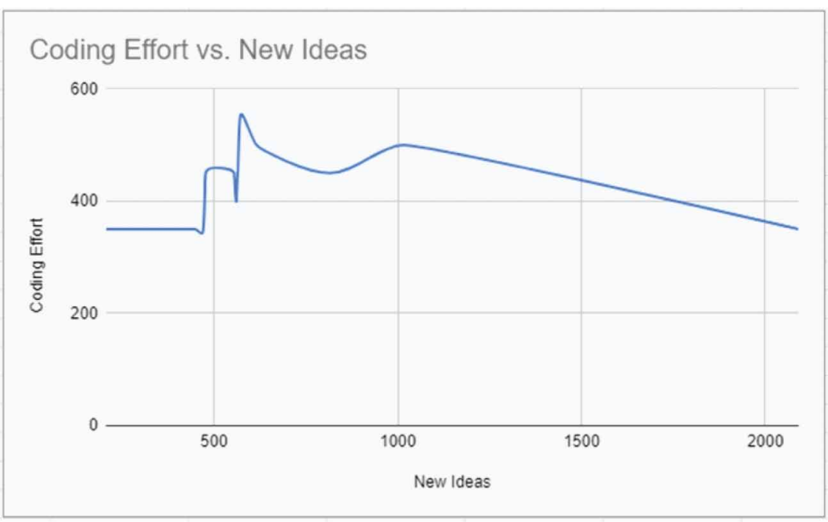
Figure 9. Changing Strategy Points. Explorers vs. Achievers



mind-set behaviour. The students responded positively to being rewarded for exploration scoring an average of 65% above the baseline score.

However, *New Ideas* points appear to be beneficial up to a point. Figure 10 shows the relationship between *Coding Effort* points and *New Ideas* points. The line graph shows a changeable relationship with a Pearson correlation co-efficient of 0.02 suggesting that there is no relationship between the two. However, figure 10 does show a rising relationship initially followed by a steady drop as the students become more productive. Furthermore, when the high and low performing students are taken alone, there is a Pearson correlation co-efficient of 0.73 for the low performing group and -0.91 for the high performers. This demonstrates that awarding points for exploration of new blocks is effective up to a point and becomes less effective as productivity increases. Consistent with Plass et al., (2014), students will benefit from being rewarded frequently in the beginning and will gain less from being incentivised as the game progresses.

Figure 10. Relationship Between New Ideas Points and Coding Effort Points



Through the lens of Bartle's Taxonomy, it was expected that the students who exhibited Explorer behaviour towards *Changing Strategy* would also be more inclined to experiment with new blocks of code. Figure 11 shows that these Explorers naturally experimented with new blocks at a much higher rate than Achievers as the study progressed as they are interested in figuring out how things work (Bartle 1996). With the exception of week 1, where Achievers completed more levels, Explorers experimented more and accelerated their experimentation at a higher rate than Achievers. However, the Achievers *New Ideas* scores continued to rise as the intervention progressed suggesting that the points awarded for exhibiting experimentation were incentive enough to motivate Achievers to exhibit this growth mind-set behaviour. This suggests that *Changing Strategy* points and *New Ideas* points complement each other particularly with Achievers as they are less likely to exhibit these growth mind-set behaviours unless they are incentivised to do so.

It was expected that Achievers would score higher *Coding Effort* points than Explorers at all stages throughout the intervention. By the end of the study, this turned out to be the case. However, figure 12 shows that the average *Coding Effort* scores for Achievers in week 3 was lower than the

Figure 11. New Ideas Points. Explorers vs. Achievers

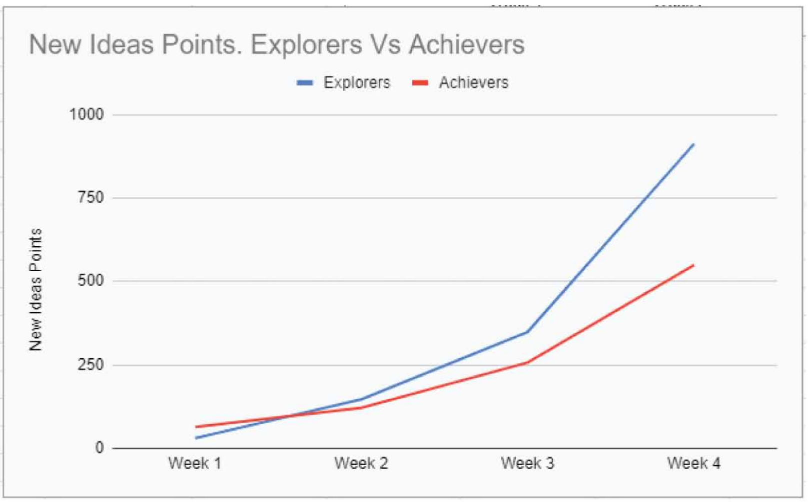
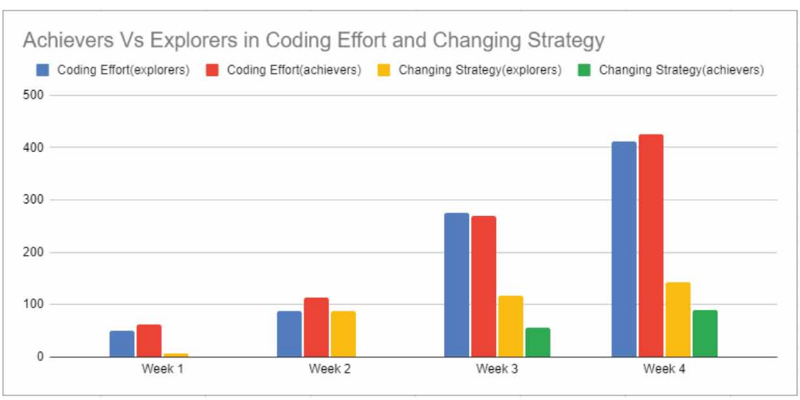


Figure 12. Achievers and Explorers in Coding Effort and Changing Strategy



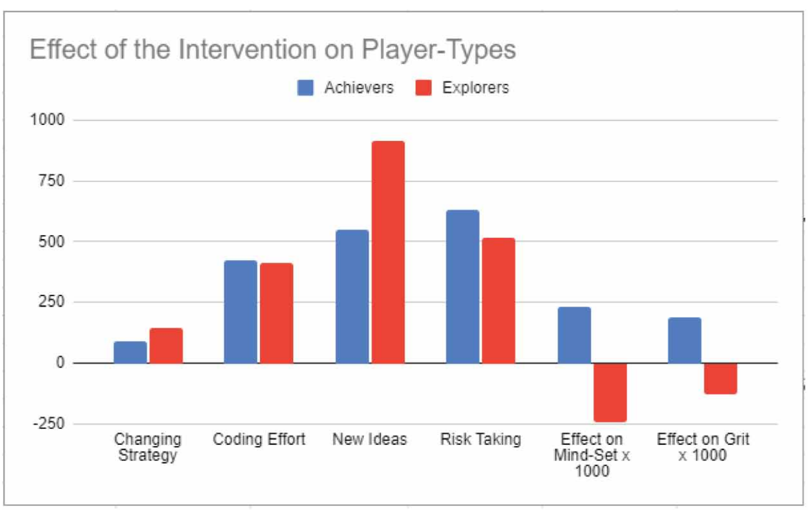
Explorers. Furthermore, figure 12 shows that Achievers began to score *Changing Strategy* points in week 3. This suggests that in week 3, Achievers began to recognise that these growth mind-set behaviours are valued and incentivised in the game and that in order to continue to score points and progress through the levels, that these behaviours require their focus in order to maximise their scores (Zenn 2017). In contrast, figure 12 shows that Explorers experienced a consistent success rate as a result of their curiosity in to what the help modals had to offer. In keeping with Burmester (2020), this suggests that Explorers are more likely to exhibit the growth mind-set behaviour of changing strategy in the face of challenge while also being less influenced by gamification.

It was expected that the intervention would had a larger effect on Achievers than Explorers as Achievers are highly motivated by gamification while Explorers are less so. Figure 13 shows that Explorers scored higher in *Changing Strategy* and *New Ideas* points while Achievers scored higher in *Coding Effort* and *Risk Taking* points as discussed above. However, the intervention had a surprising effect on the mind-set of Explorers. Figure 13 shows that the intervention had a negative effect on Explorers as their post survey scores were lower than their pre survey scores. This may be due to the fact that the game was primarily focused on using gamification to incentivise players and Explorers view scoring points as a means to an end and not an end in itself (Bartle 1996). In contrast, Figure 13 shows that the Achievers responded positively in post survey scores demonstrating that gamification is effective at incentivising growth mind-set behaviour and improving the mind-set and grit in Achievers as this player-type is highly motivated by achieving status within the game by accumulating point by moving through the levels (Burmester 2020). Furthermore, this shows that Achievers have been much more influenced by being incentivised to exhibit growth mind-set behaviours as they tend to follow the games rules so that they acquire the highest scores at the expense of all else and are easily encouraged to work hard in the pursuit of status and victory (Zenn 2017).

5. CONCLUSION

Using gamification to incentivise growth mind-set behaviour in Junior Cycle Coding students resulted in increases in many behaviours desirable when learning to computer program and improved the growth mind-set of the focus group by a small amount, replicating the findings of Cutts et al., (2010) and Quille and Bergin (2020). The data shows that the intervention had a positive effect on mind-set,

Figure 13. Effect of Intervention on Player-Types



a significant effect on the grit, particularly on the perseverance of effort of the focus group relative to the control group and that the growth mind-set behaviours rose significantly as the study progressed.

Furthermore, gamification has shielded the focus group from the negative effects that learning to code had on the mind-sets of the control group. Consistent with Flannigan et al., (2016), the data showed that learning computer programming moved the average mind-set of the control group towards a fixed mind-set while also having a negative effect on grit scores with perseverance of effort the most significantly impacted.

In keeping with O'Rourke et al., (2016), this study has demonstrated that awarding points for growth mind-set behaviours is an effective method of incentivising persistence, productive struggle and a mastery response to challenge by changing strategy. However, consistent with Vygotsky (1963), this research has shown that the incentive structure was only effective when the rules of the game demanded it. The data shows that points alone were insufficient to incentivise risk taking, particularly with Explorers as coins held no element of surprise after collecting the first one (Zenn 2017). Furthermore, in keeping with Dweck (2017), most students chose to avoid the risk of collecting coins as the danger of colliding with an obstacle was too great. Therefore, combining the incentive structure with the rules of the game is more effective at incentivising growth mind-set behaviour than points alone.

Furthermore, the data reveals that the mind-set that a player held prior to the intervention influenced how they responded to taking risks. Consistent with Dweck (2017), the student's holding a strong growth mind-set chose the more difficult task and collected coins while the others chose the easier task and ignored the coins on their way to the finish line. Therefore, the coin collection game element was ineffective at incentivising risk taking behaviour with students who did not hold a strong growth mind-set to begin with.

Moreover, risk taking and the level complete modals have been shown to be unattractive to Explorers in its current form. The fact that Explorers are not intrinsically motivated by scoring points has led to the collection of coins and the repeating of levels being ignored by this player-type (Zenn 2017).

Kizilcec and Goldfarb (2019) argued that when students with a fixed mind-set are faced with a challenge, they are likely to exhibit a helpless response to failure. This study revealed that when students are rewarded for showing a mastery response to challenge by receiving points for using the help modal, that their use of the help modal will increase in frequency as the level of challenge increases. Furthermore, this research has shown that, regardless of mind-set, gamification is an effective method to incentivise a mastery response to challenge. Additionally, player-type has been shown to influence how the participants experiment with new code and use the digital MKO. While the Explorer has a natural inclination to experiment with all the features that the game has to offer, the Achiever initially viewed the help modal and experimentation with new blocks as an unnecessary delay until they discovered that they were incentivised to do so. This shows that the gamification of growth mind-set behaviours in computer programming tasks is more effective at modifying the growth mind-set behaviour of Achievers than Explorers.

Additionally, this research has shown that gamification is more effective at influencing mind-set and grit of Achievers than Explorers. While Explorers intrinsically experiment with strategy and new blocks, gamification has no positive influence over them. In contrast, Achievers are highly susceptible to gamification as they demonstrated increases in growth mind-set behaviours to score points through actions that are unnatural to them. The fact that Achievers are motivated by points has been instrumental in improving their mind-set and grit as they modified their behaviour to gain rewards and, in turn, boosted their mind-set.

The results of this research are significant as they demonstrate an effective pedagogy to teach Junior Cycle Coding that prevents the negative impact that learning to code has on a student's ability to persist, to change strategy when in difficulty and to demonstrate a mastery response to challenge. The findings of this research may benefit teachers setting out on their path to becoming Leaving

Cert Computer Science teachers where their students are likely to be inundated with syntax and logic errors. CS teachers would benefit from the knowledge that providing an avenue to get help when stuck and rewarding students when they use it, leads to that behaviour being sustained and repeated more frequently as these rewards continue.

6. LIMITATIONS

Due to the disadvantaged nature of the school at the centre of this research, the number of students involved in the research was small. Furthermore, with the outbreak of covid-19, a number of participants did not engage in all elements of the intervention and their data was not included as a result.

While every effort was made to ensure all students has the same amount of time playing the game, some students has less exposure to the game than others. The study took place over a short period where students played the game for the last 10 minutes of each lesson and the difference in exposure time may have affected the results in a minor way.

The multifaceted nature of this intervention may present some ambiguity around which component drove which effect. For example, all components had the intention of influencing growth mind-set and behaviour which leaves some uncertainty as to which component was most influential.

7. RECOMMENDATIONS

A study of a much larger scale over a longer period would offer more validity and reliability to the findings in this research. Conducting this research with students with a broader age profile would be useful in determining if this intervention had the same impact on students that were older and younger.

Further research is needed to determine how effective each game element would be in isolation to determine how well they incentivise their intended growth mind-set behaviour without the combined impact of the other game elements. Furthermore, conducting research where the game elements are used in different combinations would be useful in determining which mixture would have the greatest impact on growth mind-set results and behaviours.

Further research is needed to determine an effective method of incentivising challenge seeking behaviour with children holding a fixed mind-set. It may be useful to determine if exposure to an intervention similar this kind would eventually lead to risk taking behaviour. Additionally, research is needed to discover how to positively influence the mind-set Explorers and lead to improvements in growth mind-set behaviours in computer programming tasks.

REFERENCES

Bartle, R. (1996). Hearts, Clubs, Diamonds, Spades: Players Who Suit MUDs. *Journal of MUD Research*, *1*(1), 19.

Brooks, C., Kizilcec, R. F., & Dowell, N. (2020). Designing Inclusive Learning Environments. *Proceedings of the Seventh ACM Conference on Learning*, 225-228. doi:10.1145/3386527.3405935

Burmester, N. (2020). *The Bartle Test of Gamer Psychology - Gamer Types*. Gamify. https://www.gamify.com/gamification-blog/the-make-up-of-gamers-the-bartle-test-of-gamer-psychology

Burnette, J., Hoyt, C., & Russel, M. (2019). A Growth Mind-Set Intervention Improves Interest but Not Academic Performance in the Field of Computer Science. *Social Psychological & Personality Science*, *11*(1), 107–116. doi:10.1177/1948550619841631

Claro, S., Paunesku, D., & Dweck, C. (2016). Growth mindset tempers the effects of poverty on academic achievement. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(31), 8664–8668. doi:10.1073/pnas.1608207113 PMID:27432947

Cutts, Q., Cutts, E., Draper, S., O'Donnell, P., & Saffrey, P. (2010). Manipulating mindset to positively influence introductory programming performance. *Proceedings of the 41st ACM technical symposium on Computer science education*, 431-435. doi:10.1145/1734263.1734409

Duckworth, A. L., Peterson, C., Matthews, M. D., & Kelly, D. R. (2007). Grit: Perseverance and passion for long-term goals. *Journal of Personality and Social Psychology*, *92*(6), 1087–1101. doi:10.1037/0022-3514.92.6.1087 PMID:17547490

Duckworth, A. L., & Quinn, P. D. (2009). Development and validation of the Short Grit Scale (GritS). *Journal of Personality Assessment*, *91*(2), 166–174. doi:10.1080/00223890802634290 PMID:19205937

Dweck, C. S. (2016). What Having a "Growth Mindset" Actually Means. *Harvard Business Review.* https://hbr.org/2016/01/what-having-a-growth-mindset-actually-means

Dweck, C. S. (2017). *Mindset – Updated addition: Changing The Way You Think To Fulfil Your Potential*. Penguin Group.

Dweck, C. S., & Yeager, D. S. (2019). Mind-sets: A View from Two Eras. *Perspectives on Psychological Science*, *14*(3), 481–496. doi:10.1177/1745691618804166 PMID:30707853

Ehrlinger, J., & Mitcham, A. (2015). Understanding overconfidence: Theories of intelligence, preferential attention, and distorted self-assessment. *Journal of Experimental Social Psychology*, *63*, 94–100. doi:10.1016/j.jesp.2015.11.001

Flanigan, A. F., Peteranetz, M. S., Shell, D. F., & Soh, L. K. (2016). Implicit intelligence beliefs of computer science students: Exploring change across the semester. *Contemporary Educational Psychology*, *48*, 179–196. doi:10.1016/j.cedpsych.2016.10.003

Fleming, U., & McInerney, C. (2019, February). *Junior Cycle Coding in Action– a CPD initiative to support the introduction of the Junior Cycle short course Coding.* Interim Report. https://lero.ie/sites/default/files/2019_TR_04_Junior%20Cycle%20Coding%20in%20Action%E2%80%93%20a%20CPD%20initiative%20to%20support%20the%20introduction%20of%20the%20Junior%20Cycle%20short%20course%20Coding.pdf

Gerstein, J. (2013). *Learner Agency, Technology, and Emotional Intelligence.* User Generated Education. https://usergeneratededucation.wordpress.com/2013/01/04/learner-agency-technology-and-emotional-intelligence/

Johnson, C., McGill, M., Bouchard, D., Brsdshaw, M. K., Bucheli, V., Merkle, L. D., Scott, M. J., Sweedyk, Z., Angel, J., Xiao, Z., & Zhang, M. (2016). *Game Development for Computer Science Education.* https://dl.acm.org/doi/10.1145/3024906.3024908

Kinnunen, P., & Simon, B. (2011). CS majors' self-efficacy perceptions in CS1: results in light of social cognitive theory. *Proceedings of the seventh international workshop on Computing education research*, 19-26. doi:10.1145/2016911.2016917

Kizilcec, R., & Goldfarb, D. (2019). Growth Mindset Predicts Student Achievement and Behavior in Mobile Learning. *ACM Conference on Learning @ Scale, 8, 1-10*. doi:10.1145/3330430.3333632

Limeri, L. B., Carter, N. T., Choe, J., Harper, H. G., Martin, H. R., Benton, A., & Dolan, E. L. (2020). Growing a growth mindset: Characterizing how and why undergraduate students' mindsets change. *International Journal of STEM Education*, *7*(1), 35. doi:10.1186/s40594-020-00227-2

Mueller, C. M., & Dweck, C. S. (1998). Praise for intelligence can undermine children's motivation and performance. *Journal of Personality and Social Psychology*, *75*(1), 33–52. doi:10.1037/0022-3514.75.1.33 PMID:9686450

Murphy, L., & Thomas, L. (2008). Dangers of a Fixed Mindset: Implications of Self-theories Research for Computer Science Education. *ACM SIGCSE Bulletin, 40*(3), 271-275. https://dl.acm.org/doi/10.1145/1384271.1384344

O'Rourke, E., Haimovitz, K., Ballwebber, K., Dweck, C., & Popovi, Z. (2014). Brain Points: A Growth Mindset Incentive Structure Boosts Persistence in an Educational Game. *CHI '14: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 3339-3348. doi:10.1145/2556288.2557157

O'Rourke, E., Peach, E., Dweck, C. & Popovic, Z. (2016). Brain Points: A Deeper Look at a Growth Mind-set Incentive Structure for an Educational Game. *ACM Conference on Learning at Scale*, 41-40. 10.1145/2876034.2876040

Park, H., Rosenberg-Kima, R., Gordan, G., & Rosenburg, M. (2017). Growing Growth Mindset with a Social Robot Peer. *HRI '17: Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*, 137-145. doi:10.1145/2909824.3020213

Parker, M. C., Solomon, A., Pritchett, B., Illingworth, D. A., Marguilieux, L. E., & Guzdial, M. (2018). Socioeconomic Status and Computer Science Achievement: Spatial Ability as a Mediating Variable in a Novel Model of Understanding. *Proceedings of the 2018 ACM Conference on International Computing Education*, 97–105. doi:10.1145/3230977.3230987

Pinkard, N., Erete, S., Martin, S., & McKinney de Royston, M. (2017). Digital youth divas: Exploring narrative driven curriculum to spark middle school girls' interest in computational activities. *Journal of the Learning Sciences*, *26*(3), 477–516. doi:10.1080/10508406.2017.1307199

PISA. (2018). What School Life Means for Students' Lives. *OECD iLibrary, 3*(14). https://www.oecd-ilibrary.org//sites/bd69f805-en/index.html?itemId=/content/component/bd69f805-en#

Plass, J., Homer, B., & Kinzer, C. (2014). *Playful Learning: An Integrated Design Framework*. Games For Learning Institute. doi:10.13140/2.1.4175.6969

Plass, J., Homer, B., & Kinzer, C. (2015). Foundations of Game-Based Learning. *Educational Psychologist*, *50*(4), 258–283. doi:10.1080/00461520.2015.1122533

Quille, K., & Bergin, S. (2020). Promoting a Growth Mindset in CS1: Does One Size Fit All? A Pilot Study. *Proceedings of the 2020 ACM Conference on Innovation and Technology in Computer Science Education,* 12-18. https://dl.acm.org/doi/pdf/10.1145/3341525.3387361

Ryoo, J. (2019). Pedagogy that Supports Computer Science for All. *ACM Transactions on Computing Education*, *19*(4), 1–23. doi:10.1145/3322210

Simon, S., Hanks, B., Murphy, L., Fitzgerald, S., McCauley, R., Thomas, & Zander, C. (2008). Saying isn't necessarily believing: Influencing self-theories in computing. *Proceeding of the fourth international workshop on Computing education research*, 173–184. doi:10.1145/1404520.1404537

Von Davier, T. S. (2019). Betacritic: Blockly Maze. *Medium.* https://medium.com/@tvondavi/betacritic-blockly-maze-88369fa8f626

Vygotsky, L. S. (1968). *The Psychology of Art*. The MIT Press.

Vygotsky, L. S. (1978). *Mind in Society: The Development of Higher Mental Processes*. Harvard University Press.

Weinthorp, D. (2019). Block-based Programming in Computer Science Education, Considering how block-based programming environments and tools might be used at the introductory level and beyond. *Communications of the ACM*, *62*(8), 22–25. https://dl.acm.org/doi/pdf/10.1145/3341221

Yeager, D. S., Hanselman, P., Walton, G. M., Murray, J. S., Crosnoe, R., Muller, C., Tipton, E., Schneider, B., Hulleman, C. S., Hinojosa, C. P., Paunesku, D., Romero, C., Flint, K., Roberts, A., Trott, J., Iachan, R., Buontempo, J., Yang, S. M., Carvalho, C. M., & Dweck, C. et al. (2019). A national experiment reveals where a growth mind-set improves achievement. *Nature*, *573*(7774), 364–369. doi:10.1038/s41586-019-1466-y PMID:31391586

Yeager, D. S., Romero, C., Paunesku, D., Hulleman, C. S., Schneider, B., Hinojosa, C., Lee, H. Y., O'Brien, J., Flint, K., Roberts, A., Trott, J., Greene, D., Walton, G. M., & Dweck, C. S. (2016). Using design thinking to improve psychological interventions: The case of the growth mindset during the transition to high school. *Journal of Educational Psychology*, *108*(3), 374–391. doi:10.1037/edu0000098 PMID:27524832

Garry Gorman is a graduate of the Masters in Computer Science Education Research at LYIT and is currently a Computer Science and Engineering teacher at post-primary level.

Nigel McKelvey is a lecturer in Computing at the Letterkenny Institute of Technology and specialises in teaching secure programming techniques at both undergraduate and postgraduate level. Other areas of interest include ethical gaming, performance-based programming and digital forensics.

Thomas Dowling is a former lecturer in Computing and a current Head of Department of Computing.