RESEARCH ARTICLE

Modelling the Relationship between Computer Usage and Mathematics Performance Using Three Waves of the Growing Up in Ireland Study

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Introduction

Increased use of computers at home and school is current government policy in Ireland (Department of Education and Skills, 2017). Along with a continued growth of computer ownership and broadband connectivity, Ireland has seen an increase in children using computers and accessing the internet from a young age (Eurostat, 2016). This paper conducts a longitudinal exploration of the link between children’s self-reported home computer use and curriculum linked mathematics performance from age nine to fifteen years to model the long-term effects of these behaviours.

Previous research using data from the nine-year-old cohort of Growing Up in Ireland (Casey, Layte, Lyons and Silles 2012) revealed that fun, unstructured uses of the internet had a significant positive relationship with mathematics performance at nine-years-of-age. Whereas instant messaging showed a negative relationship with reading performance.

The EU Kids Online study has shown that considerable attention has been devoted to screen-time, however research on the effects of computer applications on various aspects of a child’s life is lacking (Livingstone, Haddon, Görzig and Olafsson, 2011). Recent large-scale research has underlined that screen-time itself is not particularly harmful to a child’s socio-emotional wellbeing (Orben and Przybylski, 2019a). However, there are still gaps in the literature for the effects of computer applications on areas such as academic performance to be studied (Livingstone, Mascheroni and Staksrud 2015).

The current study aims to replicate and extend the findings of Casey et al. (2012) using data from Waves One to Three of the Growing Up in Ireland - Child Cohort, accessed via the Irish Social Science Data Archive (ISSDA), to model the relationship between computer use and

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mathematics performance. In extending these findings, it is hypothesised that early social media adoption is associated with poorer mathematical performance. Similar negative effects are hypothesized for media consumption on a computer. Early social media use will be termed ‘interruptive’ computer use. High video/music consumption on computer will be termed ‘consumptive’ computer use.

It is further hypothesised that computer use by children in completing homework and independent research for completion of project work are positively associated with mathematical performance. These uses will be termed ‘informational’ and ‘independent learning’ computer applications.

Method

Participants

The Child Cohort of the Growing Up in Ireland study was used for this analysis. The longitudinal sample drew from Wave One at nine-years (N = 8,658), Wave Two at thirteen-years (N = 7,525) and Junior Certificate mathematics results at fifteen-years were derived from Wave Three (N = 6,210), (ISSDA, 2019). A longitudinal weight was corrected for study attrition (Williams, Murray, O’ Mahony and Neary, 2018a).

Measures

Control variables relating to child educational outcomes were derived from GUI publications and reports (Williams et al., 2009; Casey et al., 2012; Williams et al. 2018b). Important covariates are Household Social Class, following CSO guidelines (Thornton et al., 2011); One–Two parent Household; Highest Education of Primary and Secondary Care Giver (PCG, SCG); Child Gender; and Reading Ability at nine-years.

Self-reported computer usage comes from GUI Waves One and Two. Questionnaire wording was changed between waves reflecting changes in available technology and services. Wave One, questions about email, instant messaging and chatrooms were displaced by a question on social network use in Wave Two (Murray, Quail, McCrory and Williams, 2013).

This study also largely concerns home computer/laptop usage. Competing technologies, such as touchscreen phones and tablets, were not widely available in Ireland until shortly
after GUI Wave Two data had been collected. For instance, the Irish release of the iPad was in July of 2010 (Apple, 2010).

The Drumcondra Primary Mathematics Test was used at Wave One (ERC, 2005). The Drumcondra Numerical Ability Test was used at Wave Two (ERC, 2016). State Junior Certificate Mathematics scores were reported at Wave Three. These were adapted for use in the current study as follows: A coding scheme converted Junior Certificate Grades (A-E) and Levels (Higher, Ordinary, Foundation) to a points scale ranging from 10-100. This coding scheme has been used for parametric analysis in previous GUI reports (Williams et al., 2018a).

Mathematics performance variables were standardised to have a mean of zero and a standard deviation of one. This has several conceptual and methodological advantages for the statistical model employed.

**Statistical models**

Mplus (Muthen and Muthen, 2012) was used to develop Latent Growth Models (LGM) for this paper. LGM was used as it allows for robust estimation of results and does not require full information at each time point in order to make useful model estimates (Preacher, Wichman, MacCallum and Briggs, 2008).

In addition to standard tests for model fit, LGM captures change over time as a latent intercept (i) marking the average place a group starts, and a latent slope (s) summarizing the average change across time points as a trajectory (Geiser, 2013).

Transforming the three Mathematics performance scores to standardized variables centers the average score as zero at each time point. High and low performances are interpreted as a deflection away from an average flat trajectory, which makes interpretation of slope coefficients straightforward. Positive slopes relate to better mathematics outcomes and negative slope values relate to poorer outcomes relative to peers.

**Results**
Figure 1 below shows percentages of children using various computer applications at nine and thirteen years of age. As children entered their teens, and as computer technologies matured from the mid 2000’s, usage patterns changed. Usage of all applications except games increased. By thirteen years of age, over eighty percent used social media and over sixty percent consumed music/video on computer. There was a large increase in computers being used for homework and school projects, rising to more than sixty five percent and seventy percent respectively.

![Bar chart showing computer applications usage at 9 and 13 years]

**Figure 1.** Computer applications used at nine and thirteen years of age

LGM models were estimated beginning with a baseline model (model 1) that involved only the mathematics outcomes, from which the latent intercept and slope could be calculated. All models developed displayed excellent model fit characteristics (see Table 1) following guidelines from Hu and Bentler (1999). These consist of a Comparative Fit Index (CFI) greater than 0.9, a Root Mean Square Error of Approximation (RMSEA) less than 0.10, and a Standardised Root Mean Square Residual (SRMR) less than 0.10.
Model fit statistics from Table 1 supported the plausibility of modelling mathematics performances as a growth curve. Misspecification would result in unacceptable fit statistics from the baseline model.

Control variables were added in hierarchical steps, household covariates (model 2) captured anticipated effects of social gradients, income gradients, family structure and parental educational background that are known features of the GUI data (Williams et al., 2009).

Child level characteristics of gender and early reading ability were introduced in model 3. Fit statistics confirmed that child covariates were accurately modelled in the LGM. Williams et al. (2018b) showed that boys outperformed girls slightly in mathematical tests at nine-years-of-age, but girls begin to outperform boys on average at thirteen-and-fifteen-years-of-age. The effect at nine-years is described by a significant positive beta value for boys relative to girls on the model intercept (i) $\beta = 0.22, p < .001$. The effect of change over time, where girls begin to outperform boys is described by a significant negative beta for boys relative to girls on the model slope (s) $\beta = -0.08, p < .001$.

Figure 2 displays a simplified version of the final LGM (model 4) exploring the effects of sets of computer applications cross-sectionally at nine-years (i) and longitudinally from nine-to-thirteen-years (s). The intercept and slope are estimated as latent variables that model the effects of both internet use, and demographic variables, latent variables offer several advantages such as the ability to isolate measurement error and to cope with non-normal, or partially missing longitudinal data.
Model 4 incorporates the effects of different kinds of computer use on mathematics performance. It takes a longitudinal view by modelling the effects of technology use reported at Wave Two on the slope (s), linking patterns of computer use to changes over time in mathematical performances.

The first Section of Table 2 replicates the results of Casey et al. (2012). These showed that the child’s mathematical performance at nine-years was positively influenced by informational and independent learning uses of computers such as: ‘surfing the internet for fun’, and ‘using computers for homework/school projects’. The results also showed significant negative effects on initial mathematics performance for consumptive and interruptive styles of computer use through ‘instant messaging’ and ‘media consumption’.

<table>
<thead>
<tr>
<th>Initial effects at nine-years</th>
<th>Mathematics</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>8</td>
</tr>
<tr>
<td>School projects</td>
<td>0.09 **</td>
</tr>
<tr>
<td>Homework</td>
<td>-0.01 ns</td>
</tr>
<tr>
<td>Chatrooms</td>
<td>-0.01 ns</td>
</tr>
<tr>
<td>Application</td>
<td>Beta</td>
</tr>
<tr>
<td>---------------------------</td>
<td>------</td>
</tr>
<tr>
<td>Playing Games</td>
<td>0.13</td>
</tr>
<tr>
<td>Surfing for fun</td>
<td>0.07</td>
</tr>
<tr>
<td>Instant messaging</td>
<td>-0.20</td>
</tr>
<tr>
<td>E-mailing</td>
<td>0.10</td>
</tr>
<tr>
<td>Movies/Music</td>
<td>-0.12</td>
</tr>
</tbody>
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<table>
<thead>
<tr>
<th>Change over time</th>
<th>Mathematics (Slope)</th>
</tr>
</thead>
<tbody>
<tr>
<td>School projects</td>
<td>0.08</td>
</tr>
<tr>
<td>Homework</td>
<td>0.05</td>
</tr>
<tr>
<td>Social media</td>
<td>-0.11</td>
</tr>
<tr>
<td>Games</td>
<td>0.00</td>
</tr>
<tr>
<td>Surfing for fun</td>
<td>0.00</td>
</tr>
<tr>
<td>Movies/Music</td>
<td>-0.03</td>
</tr>
</tbody>
</table>

ns p > .05, * p < .1, ** p < .05, *** p < .001

Table 1. Model 4 Beta coefficients for Application usage

When longitudinal effects of computer use are considered, both positive and negative impacts of computer usage are seen on the model 4 slope (s). Children engaged in consumptive, or interruptive computer uses perform significantly worse over time in curriculum linked mathematics tests than those who do not use computers in this way. Children who use computers for informational purposes such as homework or project work perform significantly better in mathematics than those who do not use computers in this way.

Overall these results are quite small in magnitude but can be important when considered on a real-world scale, each represents about a fifth of a standard deviation of a difference. So, for example, if the model findings are extended to a one-hundred-item test,
where an average student scores somewhere between forty-to-sixty points, you would expect a child reporting early social media use to score two or three points lower on average than a child who does not use social media. The other statistically significant positive and negative effects reported in the model are of similar size and the effects operate independently of one another.

**Discussion, limitations and implications for future research**

This paper presents several extensions of the findings of Casey et al. (2012). Firstly, the original findings are replicated cross-sectionally, and supported longitudinally with positive and negative changes in mathematical performance related to the type of computer use reported in the home. The effects of computer use cannot simply be considered as a function of ‘screen-time’ as in many other studies (Orben and Przybylski, 2019b).

Though small in magnitude, the effects reported are independent. Each small effect can contribute to an overall trend. For instance, a child consuming social media, and not pursuing informational activities is likely to perform worse than a child who balances consumptive behaviours with informational ones. The balance between computer usage types in the home should be considered in order to support a child’s mathematical development.

There are limitations around the findings in that they do not incorporate school-based computer use. There are considerable levels of control in the statistical models for the child’s home environment, but this could be extended to include school level covariates.

Other limitations of the GUI data include the fact that the questionnaire format does not permit a detailed breakdown of devices used (phone/tablet/desktop/laptop/console) or a breakdown of the applications used per device. Future research could work to quantify applications on a per device basis, though this may place an increased response burden on participants.

Avenues for future research are clear. Future Child Cohort waves of the GUI study will add information on Leaving Certificate Mathematics performance, increasing modelling opportunities and capturing the development of adult behaviours from their roots in pre-teen and teenage years.
References


Murray, A., Quail, A., McCrory, C. and Williams, J. (2013) A summary guide to wave 2 of the infant cohort (at 3 years) of growing up in Ireland, Dublin: Economic and Social Research Institute.
O’Mahony, 2020


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**Author**

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