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App clusters: Exploring patterns of multiple app use in primary learning contexts

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ABSTRACT

There has been a continuous and rapid increase in the volume of apps in recent years since tablets became widely available in schools. Tablets contain a wide variety of apps, which are used for a large range of activities and tasks, and they are used in different combinations over time. Yet, there is limited research on young children's real and varied use of apps. The variety and volume of apps accessed by young children contributes to difficulty understanding there use and the consequences of that use. This has limited understanding of how apps contribute to students' learning. Given the importance of high-quality early learning experiences, it is essential that the use of apps in schools is better understood. This paper explores young children's real varied app use through a large aggregated Australian dataset of app usage in primary schools, which has been collected automatically from approximately 15,000 Android devices over three years. The data mining methods of clustering and association rules analysis have been used to identify patterns of app use. Results show five distinct patterns of app use. Findings provide important insights into the complexity of multiple app use in the classroom. Implications of different use patterns in relation to learning and teaching are discussed.

1. Introduction

The world of educational apps is complex and highly variable in quality. Internationally, there has been a proliferation of interactive 'educational' apps (applications) designed for use on mobile devices (e.g. smartphones and tablets) and marketed to young children, their teachers and parents. There has been very little research looking into how children use these apps (see Guernsey, Levine, Chiong, & Severns, 2016; Radesky, Schumacher, & Zuckerman, 2015). A lack of critical research in this area of app use has left teachers and parents with little guidance about which apps to use and what this use might mean for learning. Given the importance of high quality early learning (see Black et al., 2017), we argue that it is necessary to capture the complexities of young children's app use to understand possible roles in and effects on learning and the wider educational context.

In this paper, we explore children's real and varied use of apps in school, to identify patterns of use and explore implications for learning and teaching. Most tablet and smartphone devices contain a wide array of apps that can be used for a range of different purposes – from social media to memory games to photo editing to reading the news. These apps support a variety of tasks and activities that a young child may engage in as part of their learning, such as reading, playing a puzzle game and searching online.

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Many apps are designed to be used on their own but are often part of a large and heterogeneous collection of apps that a child may access at any time (Domingo & Garganté, 2016). In a learning context, they may use multiple apps focusing on 'sight reading' to practice word recognition. The use of multiple apps significantly increases the complexity of app use, which complicates identification of effects of an individual app to learning. By gaining an understanding of this varied and combined use, it is possible to better understand the complexity of app use and what this means for integration in teaching, how they support learning and their role in learning design.

To explore children's combined app use in school, we first present a discussion of what is known about young children's app use, and why it is important that a more critical view is taken of app integration in learning. Patterns of app use will then be identified and analyzed. The data used in this analysis was automatically collected from 15,000 Android tablets, as part of an Australian national one-to-one 2-in-1 device (portable device with features of a laptop and tablet) program. Data mining approaches were used to analyze the usage data, to identify clusters and patterns. Results show five distinct patterns of app use: Education-focused, Paid educational, Personalized, Gendered and Non-educational. Findings suggest that similar apps are used across schools and classrooms, but the emphasis on particular kinds of apps changes between groups. Over time and in volume, these variations may have very different effects on learning. Discussion will explore these differences and address implications for teaching and learning.

1.1. Apps and app use

Young children are one of the fastest growing consumer groups of apps. By apps we mean an application specifically designed for use on a mobile device, typically a smartphone or tablet. A large and growing portion of apps available on the market are categorized as Educational. These tend to be targeted at young children, their teachers and parents. In 2014, Apple reported that 80,000 apps in the iTunes store were classified under Education- and/or learning-based (Hirsh-Pasek et al., 2015). More recently, research has shown that 80% of top-selling paid iTunes apps are in the Education category (Guernsey et al., 2016). However, there are no guidelines controlling what qualifies as 'educational.' Many apps are not created by educators and often without consideration of how children learn (Hirsh-Pasek et al., 2015). Therefore, the quality of apps is highly variable (Falloon, 2013; Haβler, Major, & Hennessy, 2016; Hirsh-Pasek et al., 2015). Regardless of this, apps continue to be popular because they are easy to individualize and target specialized learning needs, they support social networking and are generally felt to be intuitive (Haβler et al., 2016). As a result, the use of apps in education has increased steadily, but with little understanding of the real quality and possible effect on learning.

In an effort to better understand the implications of app use, there have been a number of studies classifying apps (e.g. Domingo & Garganté, 2016; Green, Hechter, Tysinger, & Chassereau, 2014; Hirsh-Pasek et al., 2015). The aim of this work has been to examine the relation of apps to learning and consider the possible effects. Domingo and Garganté (2016) identified three types of apps: Learning Skills, Informational Management and Content Learning, to examine their use in the classroom and teachers' perceptions of their impact on learning. Domingo and Garganté (2016) identified that teachers selected apps to integrate in learning, based on learning specific content, which matched with the basic aim of these apps. They found that teachers held the most positive beliefs about the use of information in learning and more open-ended apps providing new ways to learn, which related to Informational Management and Learning Skills apps. However, Content Learning apps were found to be the most commonly used apps in classrooms, in the form of 'drill and practice' activities. This preference for open-ended apps, but more dominant use of drill and practice apps, had been observed in previous studies (e.g. Kucirkova, Messer, Sheehy, & Fernández Panadero, 2014).

1.2. Apps and learning

Domingo and Garganté found that the commonly used Content Learning apps did not significantly impact on learning. They also found that Learning Skills and Informational Management apps were more likely to have a positive impact on learning. However, there is a lack of critical research into app use in learning (Falloon, 2014). One reason or this is a lack of research addressing which apps students are actually using. For example, Domingo and Garganté's (2016) research looks at teachers' perceptions of apps, not use of apps. The apps used in their analysis were identified from research or were identified as commonly used in Primary education. Where data on real app use is collected, such as Falloon's (2014) study of 18 5-year old students' use of iPads and they are using a limited number of apps, selected by the teacher (N = 45). Of the 45 apps, 20 were paid and 25 were free versions. App use was recorded using a custom-designed software that videoed tablet screens and captured app use. Falloon (2013, 2014); also, Haβler et al. (2016) have argued that the limited evidence on app use has made it difficult to identify their impact on learning. He outlines that much of the available research has focused on specific learning contexts such as English teaching or early years education, which has been largely anecdotal and has not addressed how students interact with the devices. Therefore, generalizability of results has been difficult.

Hirsh-Pasek et al. (2015) considered possible impact on students' learning from app use through the perspective of Science of Learning. They classified apps on four key pillars. The first is that an app should encourage children to be actively involved, engaged with the materials and/or process, that content should be meaningful and relevant to their lives, and that there should be capacity for social interaction. They also added that all of this should be underpinned by clear learning goals, embedded in the context. They saw these pillars as a way for educators to assess apps, but also as a design framework for creating educational apps. They stressed that various apps may rate higher or lower on different combinations of these pillars, which is not necessarily good or bad. Their framework focuses on how students are interacting with apps, rather than the type of app and what learning content may be addressed. However, Hirsh-Pasek et al.'s (2015) framework is not grounded in research looking at app use, it is drawing on other research looking at digital technology and media use in learning. While this provides a good foundation for evaluating and designing individual apps, but it does not address the practice of using apps in learning.

2. Conceptual framework

In a learning context, students will often use multiple apps in a short time. For example, Falloon's (2013) research found that students would reach the limit of one app (e.g. unable to access additional levels) and quickly move on to another. Given the variety of apps available for any aspect of learning, there are likely to be a large number of app combinations available to students. In a natural classroom setting, there would be a wider range of apps available to students used as part of instruction and in free-time (Falloon, 2013). This would result in a number of combinations of use.

The complexity of technology use in learning has been investigated in a range of contexts, such as use in digital play (Arnott, 2016), integration and change in schools (Zhao & Frank, 2003), and how students' experience online learning (Ellis & Goodyear, 2013). To consider complexity, Zhao and Frank highlight that it is necessary to "focus attention on interactions, activities, processes, and practices" (Zhao & Frank, 2003, p. 833), which can account for more of the complexities in a given learning context. Importantly, Zhao and Frank, and Falloon, all identify that digital technologies have certain affordances and will affect their context (e.g. Ruthven et al., 2009), such as young children's ways of communicating, what they learn and their self-perception (e.g. Falloon, 2015; Olson et al., 2018; Palmér, 2015). By considering app use as a practice, beyond the use of a single app, the range of apps used by young children can be taken into consideration. A collection of apps, or groups of apps commonly used, will This is an important distinction in app use because they are rarely used in isolation in learning.

An inductive data mining approach was used to identify patterns of app use and app ecologies. Data mining is the process of discovering information and knowledge in large datasets (Tan, Kumar, & Srivastava, 2004). Where traditional statistical approaches are deductive and seeks to fit data to a model, data mining is inductive and allows for discovery of knowledge as it occurs in data (Breiman, 2001). Data mining does not assume a model; rather, patterns and anomalies are found in data and models can be derived from these findings (Baker, 2010).

To better understand patterns of use in the classroom, we draw on Domingo and Garganté's (2016) three type classification of apps, as a first step in understanding what apps comprise and what multiple app use might mean for learning. The research questions guiding this inquiry are:

1. What app types are used most frequently?
2. What are the different patterns of app use?
3. How might multiple app use relate to learning?

The current analysis seeks to understand the collection of apps students are using and the patterns of this use. Broadly, this will allow an initial view of potential "interactions, activities, processes and practices" (e.g. Zhao & Frank, 2003, p. 833) related to patterns of app use, ecologies and suggest implications for learning. However, given the breadth of this investigation, the current discussion only considers a first step in this process: if there is an explicit and direct relation to what is being learned. Subsequent work will go into more depth and nuance of how learning may happen. Results from the current analysis will be able to inform students' real use of apps and begin to unpack implications for app ecologies in the classroom.

3. Approach and methods

App use data was collected as part of an Australian Research Council (ARC) Linkage grant (2015–2018), which was a partnership between three universities and an industry partner, One Education. One Education was a non-profit company, which was previously One Laptop per Child Australia associated with One Laptop Per Child International (OLPC). The aim of the One Education program was to bring the power of technology to those most in need (One Education, 2017). This is similar to many one-to-one laptop programs, happening internationally (Howard & Rennie, 2013). The wider aim of the ARC research project was to study digital inclusion through participation in a one-to-one laptop program.

3.1. One Education participants

One Education provided low-cost purpose-built Android tablet devices to schools across Australia. A large percentage of these schools were classified as 'disadvantaged' (Howard & Rennie, 2013). In 2016, One Education was using OLPC XO devices (see OLPC, 2017). The XO was a 2-in-1 device, in that it had the functionality of a tablet and laptop (e.g. touchscreen and keyboard). The device had been designed by OLPC to be low-cost, durable, to withstand heat and dust, and to be used by children. It primarily ran on a custom-built object-oriented Sugar operating system. It was designed for younger children and generally distributed to teachers in preschool to Year 6, which included students aged 4 to 12 in Australia. However, One Education chose to install Android on the XO device. One Education included a range of educational and productivity apps on the devices, such as Reading Eggs and Word Perfect. Additional apps could be downloaded through the One Education online store, Google Play or Android APK sites.

The One Education program differed from many typical one-to-one laptop and OLPC programs. Schools could purchase the XOs, but a requirement was at least one teacher had to agree to have the XO devices in their classroom and participate in training. Upon agreeing to participate, teachers would be provided with a XO device. The same one the students would be using. They had to complete a 15-h online training, which focused on how to integrate the device in learning rather than how to use it. When this was completed they were provided with a full classroom set of the devices or however many their school had ordered. A classroom set would typically include 25–28 devices. A full description of the program is provided in Howard and Rennie (2013).

Up to 2017, the One Education program included a total of 317 distinct schools voluntarily participating. Of the total schools, a proportion of schools (approximately 59%) had been participating since 2009. There was considerable fluctuation in the program year to year, resulting from school attrition and student enrolment from year to year. Part of a school's participation in the One Education program was agreement that anonymous app usage data could be collected from the XO devices for research (Ethics information removed for review). The researchers worked with One Education to develop computer agents that automatically collected this data. Between 2015 and 2017, the data collection agent was installed on 50,000 XO devices, but only those with a working internet connection could send data. Of those, 30,000 reported over the two-year period and 15,000 were consistently reporting. Analysis presented in this paper only included the consistently reporting 15,000 devices. A total of 148 schools consistently used the 2-in-1 devices and were able to report from 2015 to 2017. These were included in the current analysis.

3.2. Data Sources and collection

The computer agent collected XO user data in two types: behaviour data and metadata. Behaviour data was basic usage data for the device. When an app was launched, a secondary app would record the timestamp and how long the app was open. This would happen for each app and every time an app was launched. The resulting data included: Machine ID, App name, App URL, Timestamp, and Duration of use. It was also possible to see the frequency of use when apps appeared multiple times. The secondary app held this log, which was then collected by the computer agent and sent to the One Education servers when the XO device was online.

The second data type was metadata about apps and schools. For each app, a scraper crawler would collect publicly-available app Category data from Google Play. Publicly-available school profile data (such as their Australian National Assessment Program Literacy and Numeracy (NAPLAN) score, geolocation data, and total number of students) was manually collected from the "My School" website (https://www.myschool.edu.au/) for each of the 148 schools. A full description of this method can be found in our technical paper (Yang, Ma & Howard, 2017).

3.3. Analysis

Analysis included three main stages: data mining, association rule mining and classification, for discovering patterns of app use and identifying relations to learning (see Fig. 1).

Next, we will elaborate on each stage in the order of processing.

3.3.1. Data mining

In the first stage, the data mining technique is applied for raw data aggregation, followed by feature generation and school clustering. For this, app use data is first aggregated on the school level. It was nearly impossible to identify if a XO device was used by one student or many, so it was assumed multiple students may be using a device. It was also necessary to protect individual students' identities, particularly at small schools. Therefore, student use data was aggregated at the school level. A second aggregation was based on the app Category, which was scraped from Google Play. There was not enough independence between Google Category metadata labels. Apps Categories are typically assigned by developers rather than using a standardized process. Moreover, there is no verification mechanism in Google Play to confirm Category assignment. This resulted in inappropriate and/or misleading use of categories, which complicated analysis. For example, in the raw metadata the 'Education' Category would appear in a number of forms (see Table 1).

To refine the Category, multiple linguistic forms of category labels were aggregated. This was done for Education, Action, Arcade, Brain Games, Books, Games, Puzzle, Role Playing, Sport, Simulation, Strategy, Creativity, Music & Video, Productivity and Lifestyle. Applying this logic, app Categories were reduced from 112 to 36.

The second step in this process was feature generation. The average app duration per instance of use was aggregated at the school level and manipulated as a high-level feature. However, some apps appeared less frequently across the schools but were still important. To account for these occurrences, the 'term frequency-inverse document frequency' (TF-IDF) measurement was employed. This measurement is popular in the text mining domain. It is generally used for evaluating the importance of one keyword in a given document. In the app-use context, if we consider the entire list of adopted apps from any one school as a document, then one particular app can be accordingly transferred as one keyword for this document. We therefore computed the app TF-IDF measurement as a keyword and identified its average duration of use. This allows consideration for apps that are not necessarily used as frequently as others but may be used for longer. TF-IDF was found to be more stable than School Location and School Size for clustering, and it

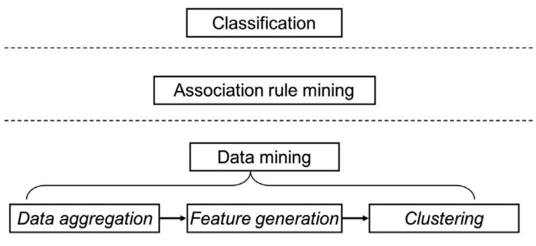

Fig. 1. Stages of analysis.

Table 1
Raw app categories from Google Play metadata.

Educational, Education
Educational
Education, Education
Education
Education, Casual

was less likely to be affected by cluster numbers (Yang et al., 2017).

The final step in this stage, was using the TF-IDF value (category frequency) as an input in a K-means-based algorithm to cluster schools. K-means algorithm is one of the most commonly used clustering algorithms in data mining. Three, five, seven and nine cluster solutions were tested. Based on a preliminary survey of apps commonly used in the clusters, in each solution, the most meaningful solution was five clusters, as it showed unique usage patterns which were less visible in the three and seven-cluster solutions. The clustering outcome was further validated by comparing the result with the same clustering method, but using school geolocation data as an input. In Australia, geolocation is commonly used to group schools and is known to correlate with performance on standardized tests (see Ainley & Gebhardt, 2003). Comparing the two outputs in terms of their predictability of NAPLAN scores, the TF-IDF clusters were found to be more predictive than geolocation. Therefore, the five-cluster solution was considered valid. Additional technical detail about this process can be found in Yang et al. (2017).

3.3.2. Association rule mining

The second stage of our analysis was different patterns of app usage in each cluster. To do this, the association rules mining algorithm was conducted to identify patterns of frequently-used App categories (see Supplemental data). Association rules mining is one of the most commonly used approaches to relationship analysis in datasets. Relationships are expressed as A - > C, where 'A' is the antecedent and 'C' is the consequence. This rule can be understood as "IF A, THEN C". An example of a rule is: "Educational > Arcade, Lifestyle". This means if Educational apps were used, then Arcade and Lifestyle apps were also used. Note that each part of a rule could also have multiple antecedents and consequences. Analysis of a dataset can result in thousands of rules, of which not all equally meaningful or important. To identify important rules, two measures are applied: confidence degree and support degree (Han, Kamber, & Pei, 2012). The confidence degree identifies how often the consequence(s) follows the antecedent(s) in a given dataset. Support degree reveals to what extents both the antecedent(s) and consequence(s) occur in the dataset simultaneously. Full definitions of these measurements can be found in Han et al. (2012). Therefore, support indicates how often the antecedent and consequent occur in a dataset, while confidence reports how often the two appear as a rule. The higher the scores, the more important the rules are in that dataset. To highlight the most significant rules, our analysis focused on rules with a large confidence degree (0.8) and a large support degree (0.7).

3.3.3. Classification

Once identifying the important rule for each cluster, we further extracted the top 10 apps for each Category, based on a composite score of Duration/Frequency to identify an average duration per use for each app. This does not necessarily indicate the top apps in each Category were the most popular overall. The top Category apps provide a sample of what important Categories comprises and patterns of use arising from multiple important Categories.

The top apps then analyzed using a 'walkthrough' method of app analysis, to identify Domingo and Garganté's (2016) three classifications for app types, by identifying "purpose, target user base and scenarios of use" (Light, Burgess, & Duguay, 2016, p. 9). This involved engaging with the app, working through the different levels and exploring general use. The three Classifications, and an additional 'non-educational' classification, were based on:

- *Learning Skills* apps can be defined as those that provide an atmosphere for students to "create their own knowledge" (Domingo & Garganté, 2016, p. 23). These apps provide an environment for students to engage in developing capacities, such as practicing writing (e.g. Writing Wizard) or drawing skills (e.g. Drawing Pad). The environments are likely to be open-ended and exploratory.
- *Informational Management* apps can be defined as those providing a specific space and/or environment to support other work, such as collaboration and informal learning. A key aspect of these apps is quick and easy access to information, such as Google Earth and Wikipedia. Learning Skills and Informational Management apps have shown to have a positive impact on learning.
- *Content Learning* which supports practice, reinforcing learning and assesses content. These may tend to be more game-like, such as Pop Maths and Eggy 100 which support practice of numeracy and literacy, respectively. This type of app is the most common and has little or limited positive impact on learning.
- The classification of *'non-educational'* was added, creating four possible classifications. This classification provides some insight into the impact different app types have one learning.

These classifications provide a common framework to classify educational apps and identify non-educational apps, so the combined use can be related to learning, compared and contrasted.

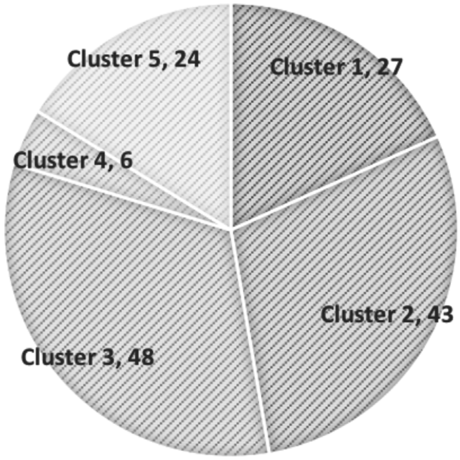

Fig. 2. Five-cluster solution.

4. Results

Results showed that students were using 30,150 apps (including the same app, but different versions) between 2015 and 2017. As outlined, data was processed and clustered on schools. The five-cluster solution was based on school distribution across the groups without clusters being too large or small (see Fig. 2).

Results of association rules analysis using app Categories revealed the rules (see Table 2).

Rules have been simplified to simply indicate Categories include. The first Category can be understood as the antecedent, with the following Categories as consequences. It can be observed that seven aggregated app Categories were important across the five clusters. Alphabetically, the categories were: Action, APK, Arcade, Education, Lifestyle, Puzzle and Tools. The full list of all top 10 app, based on longest duration per usage, in each category for each cluster can be found in the Supplemental Data File.

Table 3 outlines main features of the seven app Categories appearing in the clusters.

In the following section, each cluster will be separately discussed in relation to potential learning exhibited in each usage pattern. Category appearing in the rules will be presented with the types of apps in the category (App Description), number of apps in each type (n), if they were designed for education (Education) and Classification.

4.1. Cluster 1: Education-focused app use

Cluster 1 included 27 schools. Three categories of apps were important in this group, including Education, APK and Lifestyle. Details of apps in each category are presented in Table 4.

This cluster was defined by a strong focus on free educational apps. Seventeen of the 30 apps (57%) could be classified as Educational, based on their Category, stated learning aims and or learning content. Of those, 14 could be classified as Content Learning, which were largely 'drill and practice' apps and likely to have less impact on learning (see Domingo & Garganté, 2016). However, 3 of 17, were Learning Skills and Informational Management, which potentially have a more significant effect on learning by way of creating spaces where students could experiment and create understanding. Three apps (10%), from Lifestyle and APK, were for non-educational device personalization, e.g. wallpapers and screen-locks, and eight (27%) were non-educational games. Therefore, the majority of apps used in this cluster were educational, however they were free educational apps.

Table 2
Association rules for frequently-used app Categories.

Cluster	Name	Association rule results				
Cluster 1	Education-focused app use	education	APK[a]	lifestyle		
Cluster 2	Paid educational app use	education	arcade			
Cluster 3	Personalized app use	education	APK	lifestyle	puzzle	tools
Cluster 4	Gendered app use	action	education			
Cluster 5	Non-educational app use	action	arcade			

Note. Rules selected at the level of 0.8 confidence and 0.7 support degree.
[a] Apps downloaded from sites other than Google Play.

Table 3
Descriptions of app Categories.

App Category	Description	Example
Action/Arcade	'Game' apps, such as car racing or shooting. Does not typically claim to have a connection to educational content	Stick Man Revenge, Drag Racing, World Tanks War
Education	Numeracy or literacy related 'drill and practice' game-type apps, with some Science and Drawing apps providing a learning space for exploration.	Eggy 100, Matific, Sink or Float
Lifestyle	Generally non-educational games and personalization tools, such as wallpaper and screen-lock apps. Also, some word processing.	Launch Rex wallpaper, My Talking Tom, Word Perfect
Puzzles	Mixture of non-educational apps and educational puzzle-type games.	Candy Crush, Cybersafety
Tools	Non-educational apps for managing the Android device, such as file managers and disk cleaners.	Cleanmaster, My Photo App Lock, One GoGo file shre
APK	A label assigned to non-Google apps. These were returned as 'empty' by the crawler. Wide variation to include Education and Arcade apps.	(same app types as above)

Table 4
Cluster 1 app categories, descriptions and type.

Category	App description	*n*	Education	Classification
Education	Numeracy	4	Yes	Content learning
	Literacy	5	Yes	Content learning
	Numeracy and literacy	1	Yes	Content learning
Lifestyle	Word processor	2	Yes	Informational management
	Numeracy	1	No	Content learning
	Personalization	1	No	Non-educational
	Admin	1	No	Non-educational
	Games	5	No	Non-educational
APK[a]	Literacy	3	Yes	Content learning
	Creation	2	No	Learning skills
	Game	3	No	Non-educational
	Admin	1	No	Non-educational

[a] One app, air.com.metahaze.peeplite, could not be identified.

4.2. Cluster 2: Paid education app use

Cluster 2 included 43 schools. Two categories of apps were identified as important in this group: Education and Arcade (see Table 5).

App use in Cluster 2 was defined by the use of 'paid' apps. Four of the Education apps and one of the Arcade apps were paid content. While some of these apps may have been downloaded from free APK (non-Google Play) websites, it still resulted in 25% of the content being of paid-content quality. Falloon (2014) found that paid Educational apps were generally of a higher learning quality than free apps. App use was split between 50% educational and 50% non-educational, personalization and games.

4.3. Cluster 3: Personalization app use

Cluster 3 included 48 schools and was the largest cluster. Five categories of apps were identified as important: Education, APK, Lifestyle, Puzzle and Tools (see Table 6).

This group was typified by frequent use of Personalization apps. This was also the largest group, so this pattern would be considered the most common in the sample. Of the 14 education-related apps, five were Informational Management and Learning Skills apps, which are more likely to have a positive effect on learning. However, the majority of apps were non-educational (36, 72%), half of which were Personalization and Administration apps in the Lifestyle and Tools Categories (18, 36%; e.g. wallpapers,

Table 5
Cluster 2 app categories, descriptions and type.

Category	App description	*n*	Education	Classification
Education[a]	Puzzles	2	Yes	Content learning
	Numeracy	3	Yes	Content learning
	Literacy	4	Yes	Content learning
	Science	1	Yes	Learning skills
Arcade	Games	9	No	Non-educational
	Personalization	1	No	Non-educational

[a] One app, com.pumkin.fun, could not be identified.

Table 6
Cluster 3 app categories, descriptions and type.

Category	App description	*n*	Education	Classification
Education	Numeracy	5	Yes	Content learning
	Literacy	1	Yes	Content learning
	Numeracy and literacy	3	Yes	Content learning
	Art	1	Yes	Informational management
APK	Game	7	No	Non-educational
	Admin	2	No	Non-educational
	Creation	1	No	Learning skills
Lifestyle	Word processor	1	No	Informational management
	Game	3	No	Non-educational
	Personalization	6	No	Non-educational
Puzzle	Education	2	Yes	Learning skills
	Puzzle	5	No	Non-educational
	Game	3	No	Non-educational
Tools	Personalization	4	No	Non-educational
	Admin	6	No	Non-educational

lock-screens, file managers).

4.4. Cluster 4: Gendered app use

Cluster 4 included only six schools. While small, this group exhibited a unique pattern, so it was retained in the cluster solution. Two categories of apps were identified as important: Action and Education (see Table 7).

This cluster was defined by its gendered app use and limited use of Educational apps. Four of the Educational apps were not actually Educational. Three of these were a type of hyper-feminized app aimed at young girls and focusing on beauty, fashion and friendships. Educational claims were based on 'creativity' and 'exploration', walk-through analysis showed neither of which are significantly represented in game play. The four apps were essentially 'non-educational.' Of the Action apps, four of the top five apps were 1st person shooting games, which are typically played by boys (see Olson et al., 2018). Of these four, two had a recommended Parental Guidance (PG) rating an two were rated for Mature Audiences over 15 years (MA15+).

4.5. Cluster 5: Non-educational app use

Cluster 5 included 24 schools and is defined by its lack of Educational use. Two categories of apps were identified as important: Action and Arcade (see Table 8), both of which largely comprised games.

This cluster is defined by its use of non-educational apps, specifically games. This result does not mean schools in this cluster are not using Educational apps, but that games were being used more frequently and were more important in the cluster. This suggests non-educational games were being used, on average, more than other apps. Of the games used in this cluster, four were rated PG, two MA15 + and one was so violent it was explicitly 'unrated'.

The resulting patterns represent five different types of app use in the population (see Fig. 3). While all clusters show a significant

Table 7
Cluster 4 app categories, descriptions and type.

Category	App description	*n*	Education	Classification
Action	Arcade	9	No	Non-educational
	Social	1	No	Non-educational
Education	Literacy	1	Yes	Content learning
	Maths	2	Yes	Content learning
	Art	2	Yes	Learning skills
	Social	1	Yes	Learning skills
	Games	4	Yes	Non-educational

Table 8
Cluster 5 app categories, descriptions and type.

Category	App description	*n*	Education	Classification
Action	Games	10	No	Non-educational
Arcade	Games	10	No	Non-educational

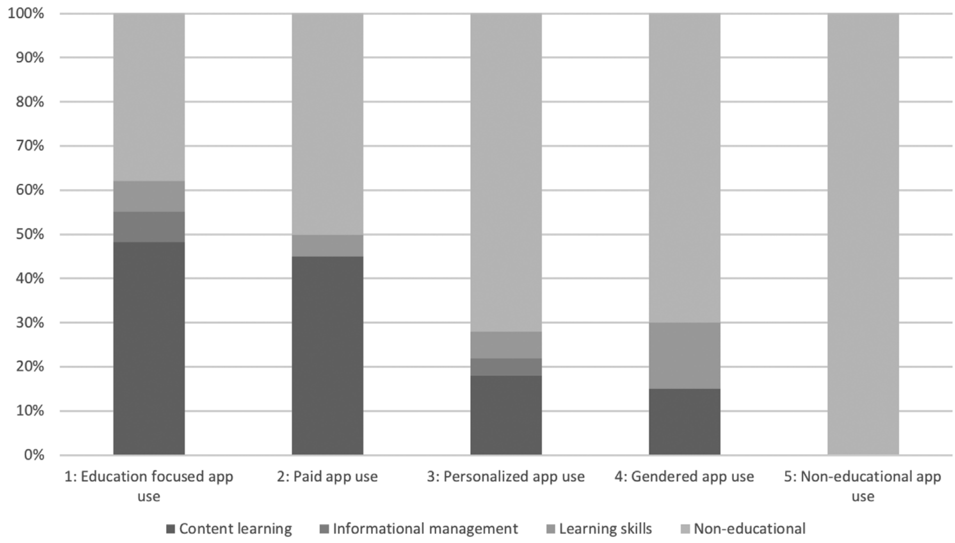

Fig. 3. App use distribution across the five clusters.

portion of non-educational app use, they do not all show educational app use. Clusters can be roughly organized by increasing emphasis on non-educational app use, coupled with a decreasing presence of educational apps. For the four clusters showing educational app use, between 15% and 5% was Informational Management and Learning Skills app use. The majority of app use was Content Learning and likely to have little educational impact.

In the following section the broader patterns will be examined and implications explored.

5. Discussion

The aim of this study was to analyze children's varied and real app use in school. Children rarely use only one app, they use collections of apps. Therefore, to understand the role and impact of apps use in learning, it is necessary to look at this combined use. To do this, computer usage data was collected from approximately 15,000 Android devices in K-6 classrooms (ages 4–12) across Australia, between 2015 and 2017. Three research questions were addressed: i) what types of apps are used most frequently; ii) what are the different patterns of app use; and iii) how might complex and multiple app use relate to learning? Five patterns of app use were identified. The main finding from this analysis was that all five cluster groups showed a wide range of combined app use and they used similar apps, but key differences in individual patterns showing emphasis on specific uses was likely to have important implications for learning.

To address research questions one and two, association rules analysis drew out the most important app uses in each group to reveal differences in combinations of apps and areas of emphasis. Two significant differences were observed. First, patterns revealed that the ratio between educational and non-educational apps gradually changed, from majority education to 100% non-educational use, between the five patterns. In the Education Focused (Cluster 1) and Paid Educational App (Cluster 2) clusters over 50% of the top apps, in the important Categories, were Educational. The majority of use was Content Learning, which has been observed in other studies (see Domingo & Garganté, 2016; Falloon, 2013). While app use in the Paid Educational app group might have been of a higher quality, the paid apps were still Content learning rather than Learning Skills or Informational Management apps. The patterns of Educational app use observed in these two group are quite typical of findings from others studies (e.g. Kucirkova et al., 2014), but it could also be argued that the majority of educational apps are Content Learning apps. Where use of Learning Skills or Informational Management apps occurred, it was typically with apps outside of the Education category, such as Minecraft (APK), coding and Word Processing (Lifestyle). It is also possible that given the breadth of literacy and numeracy Content Learning apps were used more frequently by students, while higher quality apps were used for more specific purposes. The nuance of these patterns need to be to explored more deeply to understand the balance between the three types of apps.

In Personalization and Gendered apps, each had over 70% non-educational use. However, important trends were observed here. While the five cluster groups generally used similar kinds of apps, in these two groups emphases on specific types of apps became visible in analysis. The Personalization group (Cluster 3) shows highly varied use, but with a significant amount of personalization and administrative apps from the Lifestyle and Tools categories. The majority of this use was focused on wallpapers and lock screen changes. This trend suggests students were engaged in customizing and personalizing the tablets. In this case personalization is low-level, but it is a key affordance of tablets and can contribute to increases in students' engagement in learning (Falloon, 2014). This could have an impact on how students participate in and feel about other activities performed on the device. Students may also be in the habit of locking the devices so others cannot use them if they have a dedicated tablet. However, it could also suggest a significant amount of unstructured and free-time on the devices, unrelated to any learning task. The later interpretation is possibly more accurate, given the correlating high number of games played in this group. Regardless, this is a unique trend observed in this group, which would need to be explored in more depth to understand if there is a relation to learning directly or if teachers have simply encouraged students to personalize their devices.

App use in the Gendered group (Cluster 4), while only comprising six schools, reveals a second unique pattern of classroom use. First, highly feminized apps were observed in the group. These apps were categorized as Educational and Creative. In these apps have girls engaging in apps, such as Princess Salon, Wedding Salon and Nail Salon. By using this kind of app, there is a risk of young girls adopting and accepting stereotyped female roles, which has a potentially negative effect on students' futures (Collins, 2011). Second, Arcade games rated for Parental Guidance and Mature Audiences only were also frequently used in this group. Research shows that boys are more likely to be using violent games (see DeCamp, 2017). Many of these games had hyper-masculine depictions of men, boys or other characters and associated stereotypes. Violent games appeared in other clusters, so this group is by no means isolated. However, this type of app was used more frequently and was more important in this group. While there continues to be significant debate around the effects of playing violent video games (e.g. Greitemeyer & Mügge, 2014), and we are not weighing in on that debate, it is none the less important to note the potential issues of highly gendered play and how it may affect classroom culture.

A higher occurrence of violent games was observed in the Non-educational use group (Cluster 5). Moreover, in this group Educational apps were not among the important categories. This suggests this group used the tablets for free-time or as a reward than in instruction, more than the other groups. Again, this is not to say educational or apps with a higher educational value were not used in this group but they were used more frequently than the other groups. The most important finding from this group is the emphasis on games. Further investigation is needed to identify when these games are being played, such as recess, before or after school, or during class time through an analysis of timestamping in the computer usage data. It is possible that this kind of use is not affecting classroom instruction and is strictly for students' free time. However, this raises the question of the benefit of having the device if it is not integrated in learning.

To address the third research question, differences in the five patterns of app use outlined above provide important insights into the combined app use in learning. The most commonly used apps, Content Learning and Non-Educational, are the least likely to have a positive impact on learning. However, four of the clusters include use of Learning Skills apps, which have shown to have a positive effect on learning. Two groups are using both Information Management and Learning Skills, which are both understood to have a positive effect on learning (see Domingo & Garganté, 2016). However, use of Learning Skills and Information Management apps does not necessarily relate to use of Content Learning or Non-Educational use. When considering the combined use of apps and the relation to learning, it is interesting to note that of the four groups using Learning Skills apps that use is not significantly different in terms of apps. Therefore, an initial assessment could posit that possible effect on learning would not be wildly different among four of the five groups. However, other uses may have significant effects, such as the type of apps used in the classroom space. These uses, such as over-use of personalization apps and violent games, may be important over time. Results from this analysis suggest may also be important to consider the effect of frequent use of apps with little educational impact, such as Content Learning apps. It is well known that students do not use apps in isolation and use a wide variety of digital tools in learning. The combined app use in each cluster group presents implications for learning, both in the quality of educational relation and also in how students many be using apps in their free time, that make up a whole educational experience. Looking at the combined use of apps and the pattern of app use brings into question the larger impact of apps in the classroom, beyond learning.

6. Future research and conclusions

The importance of the current findings is that the five patterns presented are drawn from real student use data and provide a basis for understanding actual app use in schools. These provide an important starting point for further critical analysis of the apps and patterns. Previously, studies looking at app use were only small and isolated groups, with potential selection bias (e.g. Falloon, 2013; Haβler et al., 2016). This study included a large nationwide population and looked at app use over several years. The data is not the result of self-reporting or observation, so it is a relatively accurate depiction of real app use in the population. Importantly, results show a range of app use in each group, which reveals significant differences in the combinations of app use and the ratio of Educational and Non-Educational apps. However, the effects in learning may be subtler, as the majority of apps used are known to have limited positive effect on learning.

However, there are limitations in the analysis. The main limitation is the use of association rules analysis to examine the clusters. Association rules only identify the most frequently occurring patterns in data, which can result in important but small patterns to be visible. Further, the association rules were based on categories. This results in seeing the most important and frequently occurring categories for each cluster but does not address the most popular apps in each cluster. These are very different results. Future analysis will consider the difference in most popular apps. An additional limitation and bias in the data is the nature of the data collection. In many schools, the XO device may have been offline or the computer agent was not able to send the usage data. Therefore, only schools where the XO device was online and data could be sent, are included in the analysis. Future work in this area will be sending USBs to non-reporting schools to 'flash' the XO devices to collect the historical usage data.

More research is needed to understand the value of apps in education and their relation to learning, which highlights the need to combined small close studies of app use patterns to be better understand the large-scale analysis. Some argue that a relational approach limits ability to generalize findings with the wider world, beyond the dataset. While patterns and relationships can be shown to exist in datasets, this does not reveal the underlying principles of these patterns which can extend findings to other contexts. With rapid increases in the number of apps categorized as Educational, but without sound educational principles and learning design, their contribution to learning cannot be assumed. Future work would aim to understand app use within an ecological model (e.g. Zhao & Frank, 2003), to unpack some of the factors guiding and shaping selection of apps and how they are used. Legitimation Code

Theory (Maton, 2014) will be used to analyze the combined app use, to look more deeply at the content and purpose of apps and implications over time in learning. Ultimately, it is not productive to say that some technology use is good and some use is bad. However, it is necessary to look at app use as a whole practice and identify how apps are positioned in teaching and learning. Findings from this research provide a solid starting point for future investigations and conversations about the role of apps, tablets and other digital technologies as part of teaching and learning practices.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.compedu.2018.08.021.

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