

Working the system: Development of a system model of technology integration to inform learning task design

Sarah K. Howard, Kate Thompson, Jie Yang and Jun Ma

Sarah K. Howard is a Senior Lecturer at the University of Wollongong. Her research looks at technology integration and teaching practice. Kate Thompson is a Senior Lecturer at Griffith University. Her research aim is to inform design for learning in complex learning environments, specifically addressing the importance of learner and instructor activities. Jie Yang is a Research Associate in the SMART Infrastructure Facility at the University of Wollongong. His research expertise is in machine learning and cloud computing. Jun Ma is a Research Fellow in the SMART Infrastructure Facility at the University of Wollongong. His research focuses on uncertain information processing and data analysis. Address for correspondence: Dr Sarah K. Howard, Early Start Research Institute, University of Wollongong. Email: sahoward@uow.edu.au

Abstract

There has been extensive investigation into factors affecting digital technology integration in learning and teaching, but the complexity of integration continues to elude understanding. Thus, questions about how digital technologies can be best used to support learning persist. This paper argues that methods designed to address complex systems are needed to understand the interplay between teaching, learning and digital technologies. Starting with a developing system model of teachers' technology integration, this study revises the model to include factors of students' experience using digital technologies and beliefs about learning. The revised model is then used to demonstrate possible effects of student experiences in a technologically integrated group learning task. Analysis draws on data from a large-scale Australian study of technology innovation ($N = 7406$). Data mining techniques are used to identify patterns of students' technology use and perceptions of group work. Findings inform revision of the model to include factors of students' experience and learning and their effects on teachers' practice. Implications for learning design and students' learning experiences are explored.

Introduction

Over the past few decades, there have been ongoing efforts to support the development of technological innovation in teaching and rigorous learning. Yet, teachers' integration of digital technology in learning continues to be inconsistent and not well understood (Borko, Whitcomb, & Liston, 2009; Perrotta, 2013). Those involved in learning analytics and educational data mining have sought to find new ways to analyze existing data about teachers' use of digital technologies and learner activity to find new answers (Pardo & Teasley, 2014); and, how results can be used to inform teachers' designs, evaluations and refinement of learning (McKenney & Mor, 2015). However, teaching and learning are social practices, and part of the dynamic and complex social system of education (Howard & Thompson, 2016). To study systems methods able to handle complexity and dynamism, and communicate findings to teachers, are needed.

In other fields, system models are widely used to test and inform complex and dynamic problems. Modelling educational systems could provide insight into the complexity of teaching and learning, but there has been minimal research in this area. In response to this gap, we previously

Practitioner Notes

What is already known about this topic

- Technology integration continues to be inconsistent among teachers and schools.
- Teaching and learning is complex and dynamic social process.
- Methods designed to handle complex and dynamic relationships among are needed to understand social systems.

What this paper adds

- A system model of technology integration including both teacher and student factors.
- Findings show that small differences in students' computer-efficacy may significantly affect learning and teaching.
- A combined method of data mining and systems thinking to research teaching and learning is presented.

Implications for practice and/or policy

- The system model can be used tool to explore complexities and effects of digital technology in group learning.
- Students' technologically integrated learning experiences are not straightforward and are not homogenous.
- Strategies for teaching and learning design, to limit negative effects of low student confidence using digital technologies, are presented.

developed a Teachers' Practice Model of Technology Integration system model ("teacher model"; see Howard & Thompson, 2016). This model focused on the process of technology integration in teaching. The aim of the model was to provide a representation of complexity among key factors of technology integration design decisions. However, while the teacher model illustrates some complexity of technology integration, it is not complete. Constructing a system model is a multi-step process. It is necessary to continually examine how systems impact on behaviours, patterns should be explored and systems should be refined as necessary. To more accurately model a teaching and learning context, teachers as well as students must be included, as they are both core to educational systems.

Therefore, the aim of this paper is to develop and inform the teacher model by including student factors of integration, using a data mining approach. Student data has been drawn from the same large-scale Australian laptop study as the teacher model. Relationships among student factors will be analyzed using educational data mining (EDM) techniques. EDM is an approach that supports the discovery of unique patterns among factors and may produce new answers to educational questions (Baker, 2010). Including student factors will create a more accurate and comprehensive model of digital technology integration, through which the complexity of technology integration and design decisions can be explored. This kind of tool can remove some of the uncertainty of changing teaching practice, which is a significant limitation in teachers' adoption and integration of digital technologies.

To do this, we will first briefly address complexity in learning and teaching, explain systems thinking and the approach in relation to technology integration. The teacher model and EDM are used to examine relations among key factors of students' digital technology use in learning. Associations among factors in the system are examined in relation to core components of design for learning: task, social arrangements (eg, group work) and resources and the learning environment

(ICT integration). To demonstrate how the resulting model can be used in teaching practice, we briefly describe two scenarios illustrating how teachers' learning design of a technologically integrated group task can be explored. The discussion will then present our next steps in system model development and future research.

Background

Modelling using systems thinking provides a way to holistically understand constituent parts of systems, see complexity and feedback, observe and test behaviour over time and how they function within a larger system. In a systems approach, identification of a problem and solution is an ongoing process. In the context of the current discussion, the problem is that technology integration in teaching and learning is still not well understood and continues to be inconsistent. In this discussion, *technology integration* can be understood as the use of digital technologies in teaching to support learning. By gaining some understanding of the complexities of technology integration, teachers can be provided with better information and support to create innovative and technologically integrated learning designs. We employ a systems approach to unpack some of the complexities of technology integration, from which possible implications, and even solutions, for supporting use of digital technologies in teaching and learning may be identified. Once a possible solution to a problem or question is identified and implemented, it must be monitored. Particularly, it is necessary to identify how gaps between the existing situation and the ideal (desired) situation may change, and new solutions may need to be identified. This process can be understood as *systems feedback thinking*, where problems and solutions coexist in an environment and are interdependent.

Historically, a common problem concerning the management of complex systems has been that when one or two influences are identified, they are assumed to be the factors responsible for observed outcomes. This has resulted in implementation of simple policies addressing those outcomes, which then fail to address more complex underlying problems (Alessi, 2000). To understand and model complex systems, a wide range of qualitative and quantitative data are used to explore problems and solutions. System dynamics models focus on explaining the structures that underlie patterns in data over time (Hirsch, Levine, & Miller, 2007, p. 245). Hirsch *et al.* (2007) used this approach to study curriculum innovation and difficulties associated with adopting innovations in education. The researchers identified that difficulties were not resulting from the innovation, but from dynamic interactions of the innovation with other aspects of a school system. Members of the school community were able to use the resulting model to test aspects of the school community, such as *Teacher Motivation* and *Trust*, which had the biggest effect on success of the innovation when adjusted. As a result, they highlight while “system dynamics cannot explain the full complexity of a system. . . system elements and interactions can produce useful insight about a problem” (Hirsch *et al.*, 2007, p. 253).

The teacher model

Difficulty understanding complex systems limits understanding of technology integration in schools. Which has resulted in a systemic focus on increasing use of digital technologies, with minimal or limited consideration for complexities of designing for learning (eg, Blackwell, Lauricella, Wartella, Robb, & Schomburg, 2013). Consequently, significant questions about how to effectively use digital technologies to support learning persist (Perrotta, 2013). A systems approach would allow key components of technology integration to be examined individually and in relation to other aspects of learning. A strength of the systems approach is the use of visualizations and common language to represent complex systems. This has proven useful when translating results to teaching and learning and supporting teachers' learning designs (Merceron & Yacef, 2010). Visualizations, such as models, can provide a way to hypothesize and test possible effects of changes in teaching and learning, in the classroom and larger educational system.

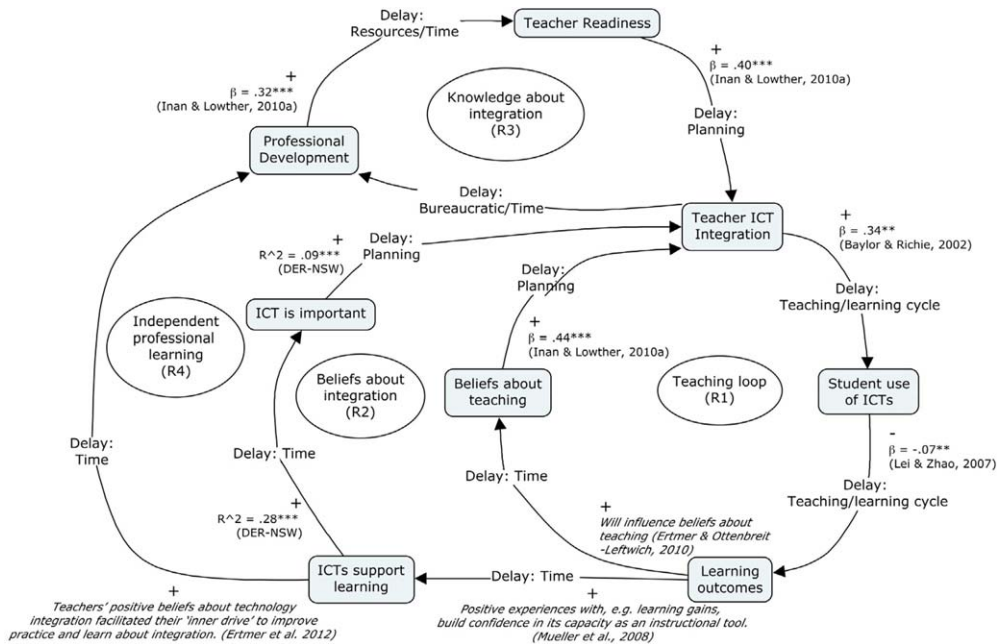


Figure 1: Teachers' Practice Model of Technology Integration (Howard & Thompson, 2016)

We have proposed that the use of models supports a refocusing from teachers' technology use to student learning *through* technology (Howard & Thompson, 2016). The teacher model presents an initial effort developing a model for this purpose (see Figure 1). A full discussion is published in Howard and Thompson (2016).

Using the teacher model, learning outcomes (R1), defined as "outcomes from students' engagement with ICT, eg, engagement, higher-order thinking skills, GPA" (Howard & Thompson, 2016, p. 1885) could be separated from beliefs about ICT supporting learning outcomes (R2). This isolates the specific relationship between student learning and learning through technology, and allows examination of how each would impact the larger system. Some research has suggested that increasing *Student Use of ICTs* without consideration to quality of integration could cause a possible negative effect on learning outcomes (eg, Lei & Zhao, 2007), which would slow the system. This was identified as an area for further investigation, as teachers' perceptions of how well students learn using a given technology has significant impact on future integration of digital technologies (Prestridge, 2012). Theoretically, balancing the effect of teachers' *Beliefs about Teaching* and *Beliefs about Integration* (R2) could influence *Teachers' ICT Integration* and students' *Learning Outcomes*, through *Students' Use of ICTs* (Howard & Thompson, 2016). By exploring factors of students' ICT use, a feedback loop at *Students' Use of ICTs* could inform students' experience in technology integrated learning and identify some possible effects on teaching.

Student experiences with ICTs

It is often assumed that young people use digital technologies without any difficulty, but actually they have minimal confidence using them for learning or in deep and/or critical ways (eg, Thompson, 2013). While they have tended to use digital technologies primarily for personal communication and entertainment, it has been found that those from higher socio-economic backgrounds are more likely to use digital technologies in sophisticated ways (Perrotta, 2013). This suggests students' experiences using digital technologies are varied and they may feel differently about technologically integrated learning (eg, Hatlevik, Guðmundsdóttir, & Loi, 2014).

How students experience technology integration will also be affected by their confidence using digital technologies, beliefs about learning and school. Howard, Ma, and Yang's (2016) framework of students' experiences in technologically integrated learning presents key factors, such as engagement with digital technologies and computer-efficacy, to consider when examining students' confidence and experiences using digital technologies in learning. They found that while the conceptual framework explained only 17% of variance in students' engagement in ICT use in school, it was identified that students with negative ICT engagement had more complex relationships with learning and engagement in school. Importantly, this finding suggests there is a risk of students becoming even less engaged in school if teachers assume they want to use ICTs.

This brings into question the practice of using digital technologies to engage students in their learning. Research has shown up to a 30% disparity between teacher and students' judgment of students' experiences in and perceptions of learning (eg, Könings, Seidel, Brand-Gruwel, & van Merriënboer, 2014). A better understanding of students' experiences in learning is needed for teachers to develop effective learning designs. Through the use of a system model, it is possible to consider the role and some effects of students' different experiences using digital technologies on teachers' decisions about integration and, by extension, their integrated learning designs.

Methods

Approach

We propose that system models are needed to examine the complexities of technology integration in teaching and learning. One aspect of this is students' experiences in a technologically integrated learning task and possible effects on teachers' design of that task. Separating tasks into component parts allows differentiation between teachers' task development processes, such as creating a lesson, and effects of the design itself (eg, components of that lesson). In our model, the *design task* is a "technologically integrated group task." An important affordance of digital technologies is thought to be the capacity to support group work (eg, Ertmer, Ottenbreit-Leftwich, Sadik, Sendurur, & Sendurur, 2012). One of the most common technologically integrated learning tasks is a group researching a topic online and constructing a report using word processing software (eg, Hsu, 2011). While this type of task is common and relatively straightforward, as with many technologically integrated tasks, little is known about students' experiences completing it.

We analyze the design task as a *design artefact*, such as a discrete lesson or unit plan, which is often different to what is enacted in the classroom (Carvalho & Goodyear, 2014). The design artefact is separated into three components: *task*, what the students are doing; *social*, including rules, roles and social arrangements; and, *resources*, physical and digital learning environment and the tools (Carvalho & Goodyear, 2014). In this paper, we focus on behaviors within the "group" *task*, possible *social* "group work" and *resources* as "digital technology integration" through an examination of key factors previously identified by Howard *et al.* (2016) as important in students' experiences using digital technologies in learning (see Table 1).

While factors such as students' efficacy with and engagement in digital technologies have been studied in depth, the current analysis takes a novel approach by analyzing factors using data mining techniques and visualizing them as a system model. The aim of data mining is *knowledge discovery*, rather than assuming a particular model. This is done through identifying unique patterns and trends in data, which can then be used to create a model. Data mining techniques "have been useful for analyzing research questions far outside the purview of what data were originally intended to study, particularly given the advent of models that can infer student attributes" (Baker, 2010, p. 113). Specifically, association analysis explores possible unique relationships and patterns among a set of factors. In this study, we consider possible associations among group learning tasks and factors of students' technology use, to expand the teacher

Table 1: Key factors of students' digital technology use in learning

Key factor	Short description
ICT engagement	The cognitive process, active participation and emotional involvement in a learning procedure using digital technologies.
Computer-efficacy	Individual's beliefs about their ability to perform future computer-related tasks.
Learning preferences	Student preferences for certain types of learning designs.
Learning beliefs	Beliefs students hold about expected learning outcomes.
ICT learning beliefs	Students' use of ICTs has a positive impact on their beliefs about the effectiveness of ICTs in their learning.
School engagement	Students' sense of belonging, happiness and feeling of support from teachers and other students.
Teacher directed ICT use	Students' beliefs about technology use are affected by teachers' attitudes towards and use of ICTs.
Frequency of ICT use	Students' ICT use in learning is directly linked to the types of tasks teachers' design.
ICT importance in subject areas	Teachers' attitudes about digital technologies differ among subject areas, thus affecting how students value and engage with ICTs.

Note. A full explanation of these factors can be found in Howard *et al.* (2016).

model. Using a system model enables work with “a range of variables including those that have been the subject of rigorous empirical research and others...[that] have not been as rigorously studied” (Hirsch *et al.*, 2007).

Research design and data collection

Using data mining approaches to extend the teacher model, we address two research questions: (1) What associations exist among factors of student experience in technology integration, and (2) How can these associations inform teachers' design of learning tasks? To investigate these questions, we used a data set from a study of the Australian Digital Education Revolution initiative in the state of New South Wales (DER-NSW; see Howard & Mozejko, 2013). The DER-NSW was a one-to-one laptop program, providing laptops for all secondary teachers and Year 9 students between 2009 and 2013. This program was evaluated between 2010 and 2013 through two online student questionnaires (A & B), a teacher questionnaire, a parent questionnaire and school case studies.

For this analysis, we draw Student Questionnaire B data from 2012. The data is considered historical and only used to explore associations among learning and technology use. In 2012, of the approximately 50 000 Year 9 (age 14–15) students in NSW government schools ($N = 436$), 21 795 (43%) completed the two-part questionnaire in 2012; 12 978 students completed Part A and 8817 students completed Part B. Questionnaire B asked students to consider the use of digital technologies in their learning. Of the 8817 students completing Part B, 7406 students responded to the question about group work and included in this analysis. Most of students had access to a computer at home (96%) and it was usually connected to the Internet (93%).

Analysis

Association analysis was conducted in three main stages: (1) factor generation, (2) creation of fuzzy sets and (3) mining of association rules. In data mining, normality of a data set is not a consideration, but the current data set can be considered normal because the sample is over 1000 respondents (Amemiya & Anderson, 1990). In brief, factors from Table 1 are aggregated and scaled to create fuzzy sets, where cases in a set have “degrees” of membership. Fuzzy sets are used

to account for unclear semantic boundaries, such as Likert-type scales, where “agree” may have different shades of meaning. Sets are then labeled with fuzzy representations, which are categorical labels using linguistic terms that represent a range of values, such as *low*, *neutral* and *high*. A full description of this procedure can be found in Howard *et al.* (2016).

Using the fuzzy representations as categorical factors, association analysis was conducted to identify possible relationships and patterns. An association (relationship) can be understood as IF A THEN C, which is commonly referred to as *rule*. Rules can also be expressed in the form of $A \rightarrow C$, where factors A and C represent the *antecedent* and *consequent* in a rule set respectively. For example, a rule can be understood as: IF a student reports low *Computer-Efficacy* (A; antecedent) THEN they may also report infrequent *Computer Use in School* (C; consequent). The importance of a rule is determined through three critical measurements: support, confidence and lift (for detailed definitions see Han, Kamber, & Pei, 2012). *Support* indicates the extent to which both the antecedent and the consequent occur simultaneously in the data set, eg, occurring in 60% of the sample. *Confidence* indicates the extent to which the consequent occurs given the presence of the antecedent, eg, a 40% chance of A occurring with C. *Lift* measures correlation between the antecedent and consequent, which is the ratio of the confidence of the rule and the expected confidence of the rule.

Results

A total of 67 rules containing *Learning Preference Group*, *ICT Engagement*, *Computer-Efficacy* and *Frequency of ICT use*, were initially identified as important (see Appendix A). The average rule support degree was 0.39, which indicates that most rules were relevant to less than 40% of the sample (see Appendix B). However, the confidence of these rules was high, averaging 82%. This suggests, while rules did not cover large portions of the sample, they were strong. The average lift for rules was 1.36, indicating that the group of participants for whom these rules apply are quite different from the rest of the population. A graph containing all important rules is presented in Appendix C.

Graphing association rules provides a way to conceptualize results and include them in a system representation, so they can be understood and tested. In this initial analysis, important rules were aggregated to simplify comparison (see Table 2) and included in a graph for further analysis (see Figure 2). Here, Table 2 presents association rules aggregated into the four main clusters (*Learning Preferences*, *Computer-Efficacy No Knowledge*, *Computer-Efficacy Low Knowledge* and *ICT Engagement*), each of which was aggregated on connections between factors within the cluster and can be described by connections between clusters. The *Frequency of ICT Use Occasional* factor has also been included, based on its theoretical position between *Learning Preferences* and *ICT Engagement* in the results. Aggregated rules between the clusters and factor include support, confidence and lift calculations (eg, 0.37, 0.84, 1.01), which represent the relative strength of associations.

Table 2: Aggregated important rules among clusters

Rule	Critical measures*
{Computer Efficacy: No Knowledge} → {Learning Preference: Negative}	0.37, 0.84, 1.01
{Computer Efficacy: Low Knowledge} → {Learning Preference: Negative}	0.37, 0.85, 1.01
{Frequency of ICT Use: Occasional} → {Learning Preference: Negative}	0.44, 0.84, 1.00
{ICT Engagement: Medium} → {Learning Preference: Negative}	0.49, 0.84, 1.00
{Computer Efficacy: Low Knowledge} → {ICT Engagement: Neutral}	0.37, 0.75, 1.02
{Frequency of ICT Use: Occasional} → {ICT Engagement: Neutral}	0.33, 0.84, 1.23

*Support, Confidence and Lift.

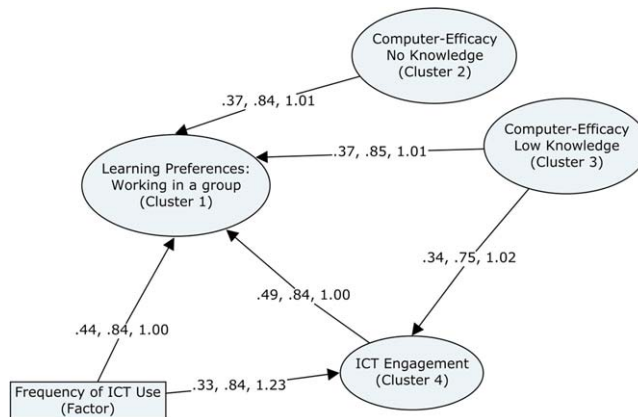


Figure 2: Aggregated graph of important rules

Computer-Efficacy No Knowledge, *Computer-Efficacy Low Knowledge*, *ICT Engagement* and *Frequency of ICT Use* all had associations with *Learning Preferences*, in relation to *Group Work* and viewed as *Negative* by students. This suggests learning preference was the most important cluster among factors. *Computer-Efficacy No Knowledge* was only associated with *Learning Preferences*. *Frequency of ICT Use* was important for students reporting only *Occasional* use and was associated with *Learning Preferences* and *ICT Engagement*, but not *Computer-Efficacy*. This suggests level of computer use did not necessarily have an effect on beliefs of ICT knowledge, but was associated with students' ICT engagement and perceptions of task group work. It should be noted that, for this initial analysis, each rule only addressed one antecedent and one consequent and they only represent between 44 and 34% of the sample, but confidence for each rule was high, between 75 and 85%. When aggregated, the lift was only slightly above 1. This indicates there was only a marginal difference between groups these rules apply to and the larger sample. However, the rule between *Frequency of ICT Use* and *ICT Engagement* had a lift of 1.23, indicating this group of students was very different from the larger sample. The graph demonstrates some complexity among associations and acts as a guide for original system model revision. In the following section, implications of associations and patterns are explored and applied to the design of learning and teaching.

Discussion

The aim of this paper was to further develop the Teacher Practice Model of Technology Integration, through the inclusion of student factors. Drawing on data mining results and conceptualizing technology integration as a design artefact, Figure 3 illustrates some of the complexity of associations among teacher and student factors and feedback in the system of technology integration.

Addressing the first research question, Figure 3 presents two refinements of the teacher model: (1) how teachers' learning design is conceptualized and (2) how students' experiences are understood in the system. First, teachers' technology integration was conceptualized as three core components of design for learning: *task* (technology integration in learning), *social* arrangements (group work) and *resources* (ICTs). Results indicate there is a critical point of interaction arising between social and resource components. This reflects a common pedagogical conceptualization of ICT integration in group tasks (Goodyear, Jones, & Thompson, 2014). This introduces a revision to the *Teacher ICT Integration* factor from the original system model (R1, see Figure 1). In the original model, integration was conceptualized at the level of a design artifact, rather than at the level of three components separating the social and resource components from the learning task.

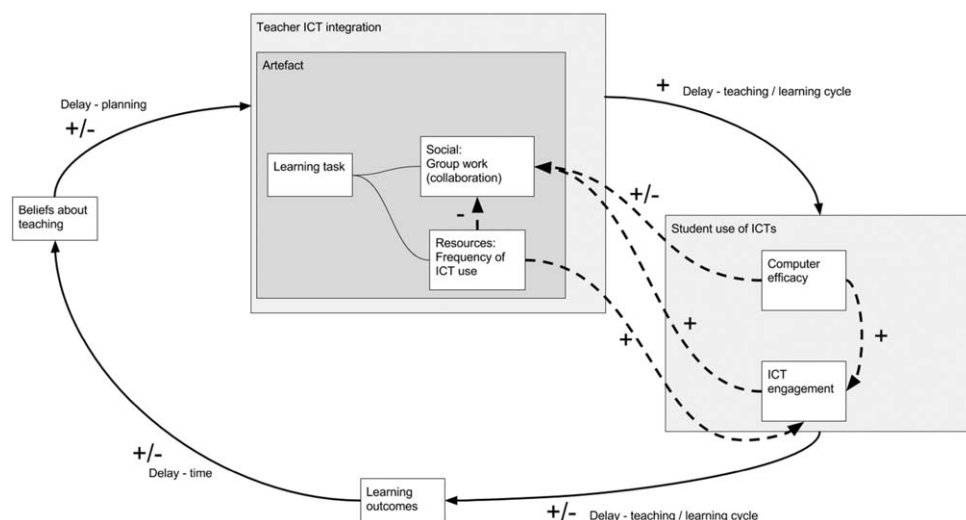


Figure 3: Revised R1 causal loop diagram

Second, data mining results revealed associations between students' beliefs about group work tasks (*Learning Preference*; social) and use of ICTs (*Frequency of ICT use*; resources), but also level of engagement with and perceptions of using ICTs. Therefore, the *Student use of ICTs* factor from the original system model (R1, see Figure 1) was similarly expanded to include associations between *Computer-Efficacy* and *ICT Engagement*. The relationship between efficacy and engagement is well researched and both factors are considered important in relation to the use of digital technologies (eg, Hatlevik *et al.*, 2014). Positive beliefs about computer-efficacy are likely to lead to engagement in digital technology use. Findings from the current analysis reflect this relationship, which demonstrates some validity of the revised model.

Organization of these factors as a system model is an important innovation. In response to the second research question, a system model approach allows for investigation of factors to explore different scenarios and solutions for problems in the system. Our revised model reveals some possible factors for consideration in learning design in relation to students' perceptions of ICTs, the relationship with the learning task and outcomes. This is different to how we normally conceptualize technologically integrated teaching in relation to teachers' beliefs and capacities, which is frequently omits students' experiences or perceptions. As both stakeholders will have an effect on the success of an integrated learning design, it is important to consider both in planning. Specifically, in the original teacher model the R1 Teaching loop (see Figure 1) suggested a positive increase in beliefs about teaching would lead to increased integration of ICT in teaching. This assumed more student use of ICTs, after a delay due to the teaching and learning cycle. We had, therefore, hypothesized that some greater use would relate to higher learning outcomes (eg, Lei, 2010), which would in turn be likely to positively influence beliefs about teaching. However, the revised model shows a more complex relationship between teachers' ICT integration and student use of ICTs, where a direct relationship between confidence using digital technologies and engagement cannot be assumed (eg, Christoph, Goldhammer, Zylka, & Hartig, 2015). Therefore, the effect on beliefs about teaching would be less predictable.

In order to understand these implications, we will take you through two scenarios. The first involves a group of students who have identified as having *No Knowledge* of computers and a teacher who holds positive beliefs about ICTs in learning (see Figure 4). The teacher designs an integrated learning task including ICTs and group work (1). This design would lead to an

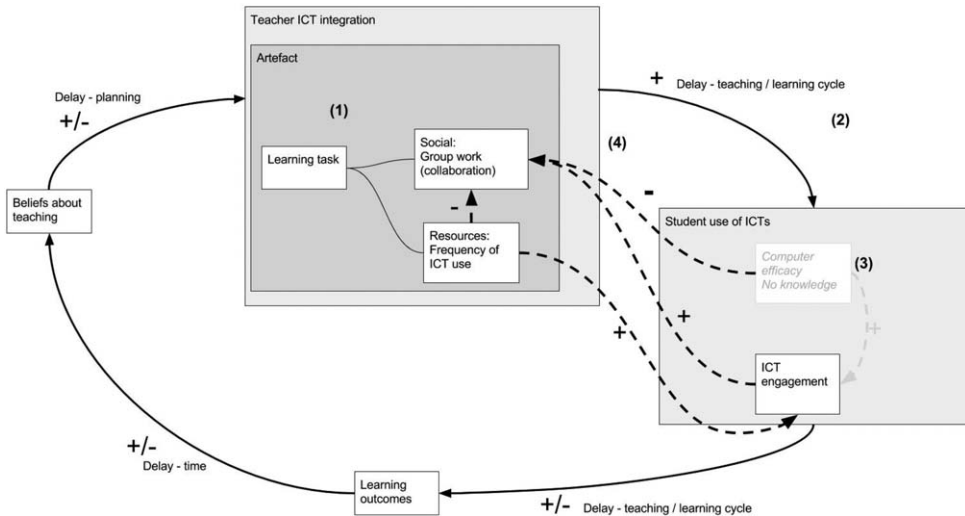


Figure 4: Revised R1 Causal Loop Diagram—Scenario 1, No Knowledge

increase in students' ICT use (2). Following common beliefs, the teacher feels this design will take advantage of students' engagement in ICT and lead to greater engagement in learning. However, for these students, computer-efficacy could be considered zero. According to our model, a relationship between computer use and engagement is not present for this group (3). The task is likely to result in increased negative perceptions of group work, as a positive feedback relationship is not present to mitigate the negative feedback loop between *No Knowledge* and *Group Work* (4). In this scenario, the model predicts that students will have a negative experience in the group work, and they are unlikely to have an increase in ICT engagement. It is, therefore, likely that learning outcomes will be affected, and subsequently would likely result in a negative effect on teacher's beliefs about technology integration.

The second scenario is more complex, as it involves a group of students who have identified as having *Low Knowledge* of computers, and a teacher who holds positive beliefs about ICT integration (see Figure 5). The teacher designs a task and decides to include ICT and group work (1). According to the model, this leads to greater student use of ICTs (2). For these students, there is the possibility of greater use of ICTs resulting in greater engagement in ICT (3). This is, however, complicated by a negative perception of learning in groups (4). Increased engagement with ICTs is related to decreased perceptions of group work. These students already have low knowledge of computers, which is related to lower perceptions of group work. However, as ICTs are used more, there are some improvements in perceptions of group work (5). The negative feedback between perceptions of group work and ICT may still have a negative effect on teachers' beliefs about teaching, but to a lesser extent than the first scenario, given a positive feedback loop exists between students' use of ICTs and learning outcomes. Learning outcomes are related to beliefs about teaching, and, in turn, will affect how teachers integrate ICT in the future.

When we examine these two scenarios, it is apparent that the solution to improving students' learning outcomes using ICT is far more complex than simply engagement with ICTs and teachers' rates of integration. Using the revised model, we imagined how an instructor would use it to investigate effects and support learning design. For example, in the design of a typical learning task using digital technologies, such as the online research task described earlier, where: the task involves working in groups, the social component is group work and the resources include the use of laptops to write a group report and create a presentation. In the task design, the teacher

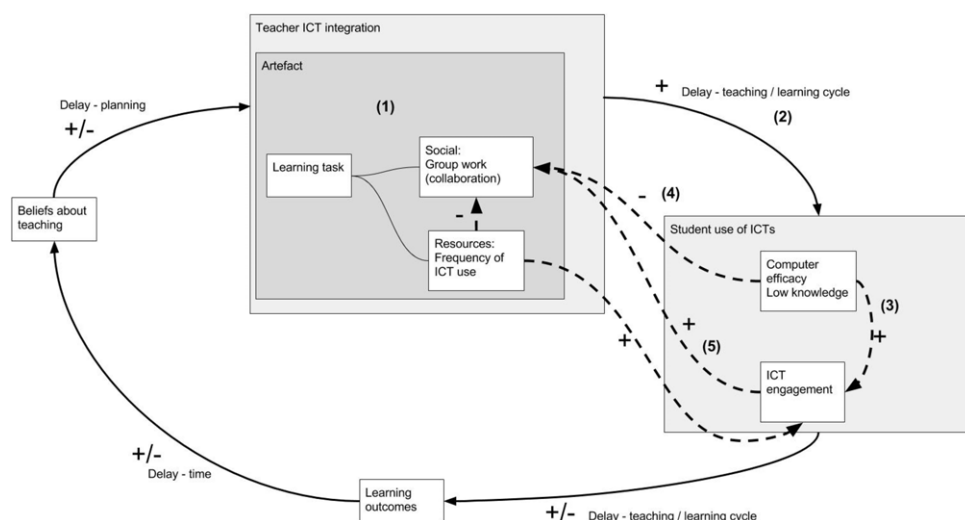


Figure 5: Revised R1 Causal Loop Diagram—Scenario 2, Low Knowledge

could consider implications for the group work such as the role of the laptops (eg, one each or in pairs). When they consider the composition of groups in the task, they can choose to let friends work together or to organize the groups in some other way, such as by ability. Care needs to be taken with the interactions of task design elements that could dampen or limit potential learning outcomes, such as students' engagement in using ICTs and how this might affect their perceptions of the group task. One approach may be inclusion of independent components in a task design, mitigating possible negative perceptions of group work. Teachers may also choose to address students' confidence and feelings of efficacy using digital technologies, as part of a task design. This approach may be problematic as many teachers believe "teaching computers" detracts from time teaching learning content, or many teachers have not felt confident using technologies themselves. Alternately, students may be assigned certain roles in the group that take their level of engagement or efficacy into consideration. These examples provide some insight into the different design considerations made visible through the revised model and just a few ways it can inform teachers' learning design and practice.

Future research and conclusions

We see exciting implications for this research, particularly in the use of the revised model in research into teaching practice and design of technologically integrated learning tasks. In particular, the model reveals some of the complex considerations involved in the use of digital technologies in learning. While we have only addressed a subset of factors, this work provides a framework for exploring effects of other factors in the system and further development of the model. For example, we would assume that other elements of the design, (such as curriculum content, physical space, prior knowledge), would also be connected and may influence learning outcomes. In addition, it could be expected that systemic factors (such as expectations around technology integration, time available to develop integrated curricula, pressure from standardized testing) would also influence teachers' decision making, and will be important areas of investigation in future model development.

Our findings introduce more questions than answers about learning through and engaging students in technologically integrated tasks. In moving forward in this work, a few considerations of the revised model need to be taken into account. The first is that association analysis is strongly

affected by sample size and bias in the data set. The data set used in this analysis, while large enough to be considered normal in traditional statistical approaches, was skewed to the negative on many of the measures. This strongly affects generation of fuzzy representations and association analysis. Further, at the time of this analysis, the DER-NSW data sets were historical and, while they can be used to explore associations among factors, new data needs to be tested in the model. To develop the revised model to try to account of these biases, the data set will be split to test different analysis processes such as refining and combining different aspects of the data. In further development of the model, additional teacher and student factors will be drawn in from the other DER-NSW data sets and future data collections. Other types of technology-supported learning designs, such as inquiry based and real-world tasks will also be investigated. While it is one thing to build on and revise the current model, further research is needed to incorporate data about teacher practice and classroom instruction, to develop predictive tools in relation to teacher and learner activity.

In this discussion, we have demonstrated how a system model can incorporate new data and deepen our understanding of existing factors. Models are flexible and open to revision, which allows growth as knowledge of a system increases. This approach is well suited to studying technology integration, as the landscape, perceptions and use in teaching and learning changes. The revised model presents an exciting early step in beginning to understand the complex process of technology integration, to support teachers' decision making and students' learning.

Acknowledgements

This research was supported, in part, by the New South Wales Department of Education and Communities. We also gratefully acknowledge the financial support of the Australian Research Council, through grant FL100100203 as well as the ideas and feedback of colleagues from the Laureate Team.

Statements on open data, ethics and conflict of interest

Data used in this publication can be accessed through the University of Wollongong. To request access, please contact the corresponding author directly.

The University of Wollongong Human Ethics Research Committee approved the research presented in this paper (HE10/007). The research was also approved by the New South Wales Department of Education (2009191).

There are no conflicts of interest in the work reported in this paper and the authors.

References

- Alessi, S. (2000). The application of system dynamics in elementary and secondary school curricular. In *Fifth Ibero-American Congress on Educational Informatics (RIBIE 2000)*. Niña del Mar, Chile.
- Amemiya, Y., & Anderson, T. W. (1990). Asymptotic chi-square tests for a large class of factor analysis models. *The Annals of Statistics*, 18, 1453–1463. Retrieved from <https://doi.org/10.1214/aos/1176347760>
- Baker, R. S. J. D. (2010). Data mining for education. In P. Peterson, E. Baker, & B. McGaw (Eds.), *International Encyclopedia of Education* (3rd ed., pp. 112–118). Elsevier. <https://doi.org/10.1016/B978-0-08-044894-7.01318-X>
- Blackwell, C. K., Lauricella, A. R., Wartella, E., Robb, M., & Schomburg, R. (2013). Adoption and use of technology in early education: The interplay of extrinsic barriers and teacher attitudes. *Computers & Education*, 69, 310–319. Retrieved from <https://doi.org/10.1016/j.compedu.2013.07.024>
- Borko, H., Whitcomb, J., & Liston, D. (2009). Wicked problems and other thoughts on issues of technology and teacher learning. *Journal of Teacher Education*, 60, 3–7. Retrieved from <https://doi.org/10.1177/0022487108328488>

- Carvalho, L., & Goodyear, P. (2014). *The architecture of productive learning networks*. NY: Routledge.
- Christoph, G., Goldhammer, F., Zylka, J., & Hartig, J. (2015). Adolescents' computer performance: The role of self-concept and motivational aspects. *Computers & Education*, 81, 1–12. Retrieved from <https://doi.org/10.1016/j.compedu.2014.09.004>
- Ertmer, P. A., Ottenbreit-Leftwich, A. T., Sadik, O., Sendurur, E., & Sendurur, P. (2012). Teacher beliefs and technology integration practices: A critical relationship. *Computers & Education*, 59, 423–435. Retrieved from <https://doi.org/https://doi.org/10.1016/j.compedu.2012.02.001>
- Goodyear, P., Jones, C., & Thompson, K. (2014). Computer-supported collaborative learning: Instructional approaches, group processes and educational designs. In J. M. Spector, M. D. Merrill, J. Elen, & M. J. Bishop (Eds), *Handbook of research on educational communications and technology* (pp. 439–451). New York: Springer.
- Han, J., Kamber, M., & Pei, J. (2012). *Data mining: Concepts and techniques* (3rd ed.). San Francisco: Elsevier Science & Technology.
- Hatlevik, O. E., Guðmundsdóttir, G. B., & Loi, M. (2014). Digital diversity among upper secondary students: A multilevel analysis of the relationship between cultural capital, self-efficacy, strategic use of information and digital competence. *Computers & Education*, 81, 345–353. Retrieved from <https://doi.org/10.1016/j.compedu.2014.10.019>
- Hirsch, G., Levine, R., & Miller, R. (2007). Using system dynamics modeling to understand the impact of social change initiatives. *American Journal of Community Psychology*, 39, 239–253. Retrieved from <https://doi.org/10.1007/s10464-007-9114-3>
- Howard, S. K., Ma, J., & Yang, J. (2016). Student rules: Exploring patterns of students' computer-efficacy and engagement with digital technologies in learning. *Computers & Education*, 101, 29–42. Retrieved from <https://doi.org/10.1016/j.compedu.2016.05.008>
- Howard, S. K., & Thompson, K. (2016). Seeing the system: Dynamics and complexity of technology integration in secondary schools. *Education and Information Technologies*, 21, 1877–1894. Retrieved from <https://doi.org/10.1007/s10639-015-9424-2>
- Howard, S. K., & Mozejko, A. (2013). *DER-NSW Evaluation: Conclusions on student and teacher engagement and ICT use*. Sydney.
- Hsu, S. (2011). Who assigns the most ICT activities? Examining the relationship between teacher and student usage. *Computers & Education*, 56, 847–855. Retrieved from <https://doi.org/https://doi.org/10.1016/j.compedu.2010.10.026>
- Könings, K., Seidel, T., Brand-Gruwel, S., & van Merriënboer, J. G. (2014). Differences between students' and teachers' perceptions of education: Profiles to describe congruence and friction. *Instructional Science*, 42(1), 11–30. <https://doi.org/10.1007/s11251-013-9294-1>
- Lei, J. (2010). Quantity versus quality: A new approach to examine the relationship between technology use and student outcomes. *British Journal of Educational Technology*, 41, 455–472. Retrieved from <https://doi.org/10.1111/j.1467-8535.2009.00961.x>
- Lei, J. & Zhao, Y. (2007). Technology uses and student achievement: A longitudinal study. *Computers & Education*, 49, 284–296. Retrieved from <https://doi.org/10.1016/j.compedu.2005.06.013>
- McKenney, S., & Mor, Y. (2015). Supporting teachers in data-informed educational design. *British Journal of Educational Technology*, 46, 265–279. Retrieved from <https://doi.org/10.1111/bjet.12262>
- Merceron, A., & Yacef, K. (2010). Measuring correlation of strong symmetric association rules in educational data. In C. Romero, S. Ventura, M. Pechenizkiy, & R. S. J. D. Baker (Eds), *Handbook of educational data mining* (pp. 245–255). Boca Raton: Taylor & Francis Group.
- Pardo, A., & Teasley, S. (2014). Learning analytics research, theory and practice: Widening the Discipline. *Journal of Learning Analytics*, 1, 4–6.
- Perrotta, C. (2013). Do school-level factors influence the educational benefits of digital technology? A critical analysis of teachers' perceptions. *British Journal of Educational Technology*, 44, 314–327. Retrieved from <https://doi.org/10.1111/j.1467-8535.2012.01304.x>
- Prestridge, S. (2012). The beliefs behind the teacher that influences their ICT practices. *Computers & Education*, 58, 449–458. Retrieved from <https://doi.org/https://doi.org/10.1016/j.compedu.2011.08.028>
- Thompson, P. (2013). The digital natives as learners: Technology use patterns and approaches to learning. *Computers & Education*, 65, 12–33. Retrieved from <https://doi.org/https://doi.org/10.1016/j.compedu.2012.12.022>

Appendix A

Table A1: Factors identified as important in perceptions of group tasks

Important factors	Description	Fuzzy representation (only those appearing in visualizations)	Example
Learning preferences: Group work	Has 4 meaningful responses [†]	Negative (LPC = negative)	Students felt negatively about how well they learned when working in groups.
Frequency of ICT Use	Has 9 meaningful responses [†]	Occasional (FIS = occasional)	Students most frequently reported using a computer at school approximately once a week.
ICT Engagement: Neutral Negative, Low Positive, Medium	Includes 4 general engagement items; each has 4 meaningful responses [‡]	Neutral (EG = neutral); Positive (EP) or Negative (EN) engagement, scored as Low (L), Medium (M); eg, Low positive engagement is EP = L)	<i>ICT Engagement Negative, Low</i> represents those students who <i>disagreed</i> (Negative) with most engagement statements, and that disagreement was <i>weak</i> (Low).
Computer-efficacy: Productivity, No knowledge§ Productivity, Low Processing, No knowledge Processing, Low Creating, No knowledge Creating, Low	Includes 10 items: Productivity tasks (6), Processing tasks (2) and Creating tasks (2); each had 3 meaningful responses§	Productivity (EP), Processing (EPC) and Creating (EC), scored as No knowledge (N) and Low (L)	<i>Computer-efficacy Productivity, No Knowledge</i> represents those students who selected “ <i>I don’t know what this means</i> ” (No Knowledge) on most of the <i>productivity</i> tasks. A “Low” label represents students who understood most of the tasks, but needed help to perform them.

[†]4 = Strongly agree, 3 = Agree, 2 = Disagree, 1 = Strongly disagree.

[‡]8 = Many times a day, 7 = Once a day, 6 = 2–4 times a week, 5 = Once week, 4 = 2–3 times a month, 3 = Once a month, 2 = Once a term, 1 = 1–3 times a year, 0 = Never.

§4 = I can do this well by myself, 3 = I can do this with help from someone, 2 = I know what this is but cannot do it, 1 = I do not know what this means.

Appendix B*Table B1: Antecedent factors important in the analysis*

<i>Antecedent factor</i>	<i># of Associations</i>	<i>Averaged support</i>	<i>Averaged confidence</i>	<i>Averaged lift</i>
Frequency of ICT Use (FIS = Occasional)	Occasional = 4	0.36	0.84	1.17
Computer-efficacy No Knowledge (EPC = N)	N = 27	0.36	0.84	1.55
Low Knowledge (EPC = L)	L = 15	0.35	0.78	1.39
ICT engagement	EN L = 5	0.44	0.96	1.28
	EP L = 1	0.31	0.85	1.01
	EP M = 5	0.40	0.82	1.14
	EG = 5	0.44	0.79	1.25
Learning preference group work	LPC N = 10	0.36	0.83	1.60

Note. Fuzzy set abbreviations (eg, EPC = L) are detailed in Appendix A.

Table B2: Consequent factors important in the analysis

<i>Consequent factor</i>	<i>Value/ Associations</i>	<i>Averaged support</i>	<i>Averaged confidence</i>	<i>Averaged lift</i>
ICT Efficacy	N = 15	0.36	0.84	1.77
	L = 11	0.34	0.77	1.67
ICT Engagement	EN L = 4	0.42	0.77	1.31
	EG = 10	0.39	0.85	1.15
Learning preference group work	LPC N = 13	0.39	0.85	1.01

Note. Fuzzy set abbreviations (eg, LPC N) are detailed in Appendix A.

Appendix C

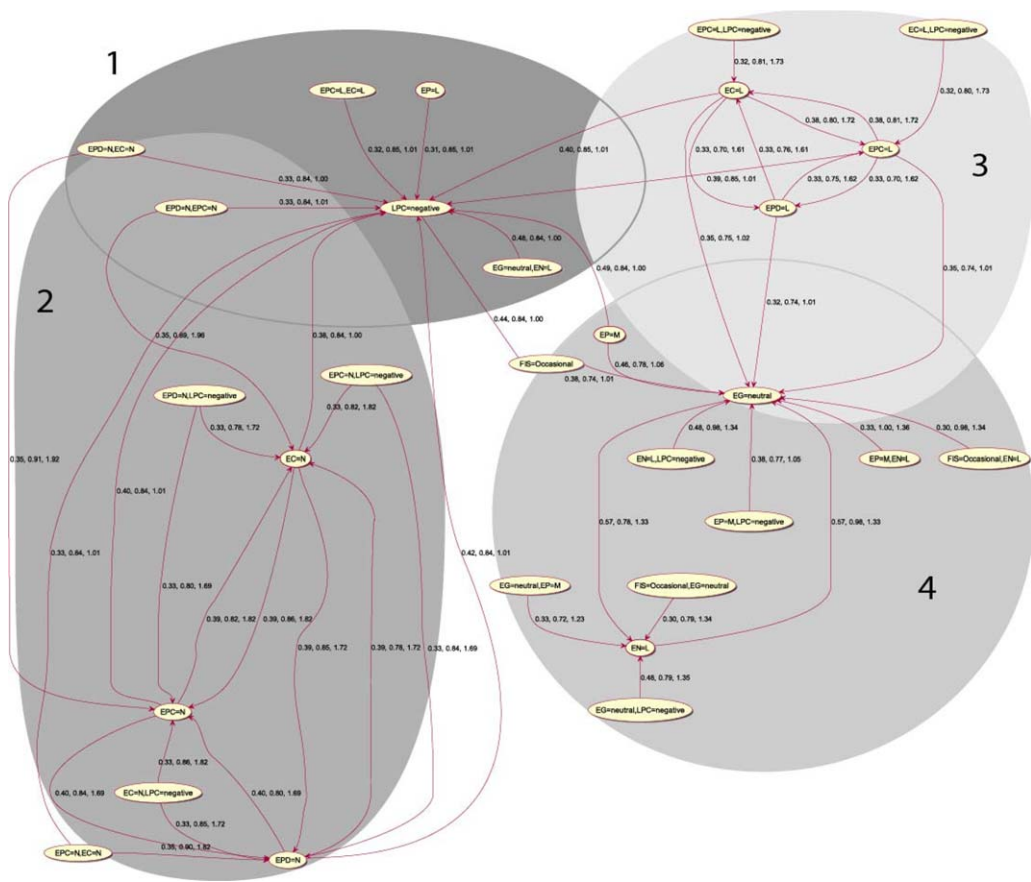


Figure C1: Clustered graph of all important rules in the data set