ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Τμήμα Ψηφιακών Συστημάτων

ΕΚΠΑΙΔΕΥΤΙΚΑ ΣΥΣΤΗΜΑΤΑ ΥΠΟΣΤΗΡΙΞΗΣ ΑΠΟΦΑΣΕΩΝ ΒΑΣΙΣΜΕΝΑ ΣΕ ΨΗΦΙΑΚΕΣ ΙΚΑΝΟΤΗΤΕΣ ΣΧΟΛΙΚΩΝ ΜΟΝΑΔΩΝ ΚΑΙ ΕΚΠΑΙΔΕΥΤΙΚΩΝ

ΔΙΔΑΚΤΟΡΙΚΗ ΔΙΑΤΡΙΒΗ

του

ΣΤΥΛΙΑΝΟΥ Ε. ΣΕΡΓΗ

Πειραιάς, 2017

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Τμήμα Ψηφιακών Συστημάτων

ΕΚΠΑΙΔΕΥΤΙΚΑ ΣΥΣΤΗΜΑΤΑ ΥΠΟΣΤΗΡΙΞΗΣ ΑΠΟΦΑΣΕΩΝ ΒΑΣΙΣΜΕΝΑ ΣΕ ΨΗΦΙΑΚΕΣ ΙΚΑΝΟΤΗΤΕΣ ΣΧΟΛΙΚΩΝ ΜΟΝΑΔΩΝ ΚΑΙ ΕΚΠΑΙΔΕΥΤΙΚΩΝ

ΔΙΔΑΚΤΟΡΙΚΗ ΔΙΑΤΡΙΒΗ

του

ΣΤΥΛΙΑΝΟΥ Ε. ΣΕΡΓΗ

Η διατριβή υποβάλλεται για την κάλυψη των απαιτήσεων

απόκτησης Διδακτορικού Διπλώματος

Πειραιάς, 2017

Στυλιανός Ε. Σέργης

Υποψήφιος Διδάκτορας Πανεπιστημίου Πειραιώς

UNIVERSITY OF PIRAEUS

Department of Digital Systems

ICT COMPETENCE-INFORMED EDUCATIONAL DECISION SUPPORT SYSTEMS FOR SCHOOL ORGANIZATIONS AND SCHOOL TEACHERS

A Thesis

Presented to

The Academic Faculty

by

STYLIANOS E. SERGIS

In Partial Fulfilment of the Requirements for the Degree Doctor of Philosophy

Piraeus, 2017

Stylianos E. Sergis

PhD Candidate, University of Piraeus

ΠΑΝΕΠΙΣΤΗΜΙΟ ΠΕΙΡΑΙΩΣ

Τμήμα Ψηφιακών Συστημάτων

ΕΚΠΑΙΔΕΥΤΙΚΑ ΣΥΣΤΗΜΑΤΑ ΥΠΟΣΤΗΡΙΞΗΣ ΑΠΟΦΑΣΕΩΝ ΒΑΣΙΣΜΕΝΑ ΣΕ ΨΗΦΙΑΚΕΣ ΙΚΑΝΟΤΗΤΕΣ ΣΧΟΛΙΚΩΝ ΜΟΝΑΔΩΝ ΚΑΙ ΕΚΠΑΙΔΕΥΤΙΚΩΝ

ΔΙΔΑΚΤΟΡΙΚΗ ΔΙΑΤΡΙΒΗ

του

ΣΤΥΛΙΑΝΟΥ Ε. ΣΕΡΓΗ

ΕΠΙΒΛΕΠΟΝ ΜΕΛΟΣ ΔΕΠ

Φωτεινή Παρασκευά, Αναπληρώτρια Καθηγήτρια, Τμήμα Ψηφιακών Συστημάτων, Πανεπιστήμιο Πειραιώς

ΤΡΙΜΕΛΗΣ ΣΥΜΒΟΥΛΕΥΤΙΚΗ ΕΠΙΤΡΟΠΗ

Δημήτριος Γ. Σάμψων, Καθηγητής, School of Education, Curtin University, Australia

Συμεών Ρετάλης, Καθηγητής, Τμήμα Ψηφιακών Συστημάτων, Πανεπιστήμιο Πειραιώς

ΕΠΤΑΜΕΛΗΣ ΕΞΕΤΑΣΤΙΚΗ ΕΠΙΤΡΟΠΗ

Φωτεινή Παρασκευά, Αναπληρώτρια Καθηγήτρια, Τμήμα Ψηφιακών Συστημάτων, Πανεπιστήμιο Πειραιώς (επιβλέπουσα)

Δημήτριος Γ. Σάμψων, Professor, School of Education, Curtin University, Australia (Μέλος Τριμελούς)

Συμεών Ρετάλης, Καθηγητής, Τμήμα Ψηφιακών Συστημάτων, Πανεπιστήμιο Πειραιώς (Μέλος Τριμελούς)

Αθανάσιος Τζιμογιάννης, Καθηγητής, Τμήμα Κοινωνικής και Εκπαιδευτικής Πολιτικής, Πανεπιστήμιο Πελοποννήσου

Σταύρος Δημητριάδης, Αναπληρωτής Καθηγητής, Τμήμα Πληροφορικής, Αριστοτέλειο Πανεπιστήμιο Θεσσαλονίκης

Χαράλαμπος Καραγιαννίδης, Αναπληρωτής Καθηγητής, Παιδαγωγικό Τμήμα Ειδικής Αγωγής, Πανεπιστήμιο Θεσσαλίας

Απόστολος Μηλιώνης, Επίκουρος Καθηγητής, Τμήμα Ψηφιακών Συστημάτων, Πανεπιστήμιο Πειραιώς

Acknowledgements

This thesis would not have been realized without the substantial support and contribution of many people, to whom I cannot but feel deeply grateful.

First of all, I thank Professor Demetrios Sampson, initial supervisor yet continuous mentor of my doctoral thesis, for his trust, insights and patience during the last 4 years; his continuous guidance to my research; and his high investment towards helping me improve myself in many ways. For all these, I am indeed thankful.

I would also like to thank my very good friend Panagiotis Zervas for supporting me throughout this process, especially during the difficult start. His advice greatly helped me to carry on.

A special thank you goes out to my close friends that were always there when I needed them. Most of all, Helen, I thank you for your everlasting care and support; you are my hero.

Last, but surely not least, I would like to express my absolute love and gratitude to my family for their everlasting love, their encouragement, and their belief to my capabilities. You made it all possible.

Stylianos Sergis

Piraeus, Greece, April 2017

Λέξεις Κλειδιά:

Εκπαιδευτικά Δεδομένα, Λήψη αποφάσεων βασισμένων σε δεδομένα, Συστήματα υποστήριξης λήψης αποφάσεων, μαθησιακή αναλυτική, διδακτική αναλυτική, ακαδημαϊκή αναλυτική, σχολική αναλυτική, ψηφιακές ικανότητες, σχολική ηγεσία, εκπαιδευτικοί σχολικών μονάδων, ηγέτες σχολικών μονάδων, μοντελοποίηση χρηστών, μοντελοποίηση ικανοτήτων εκπαιδευτικών, μοντελοποίηση ικανοτήτων σχολικών μονάδων, συστήματα συστάσεων, προφίλ ψηφιακών ικανοτήτων.

Keywords:

Educational Data, Data-driven Decision Making, Decision Support Systems, Learning Analytics, Teaching Analytics, Academic Analytics, School Analytics, ICT Competences, School Leadership, School Teacher, School Leaders, User Profiling, Teacher Competence Profiling, School Competence Profiling, Recommender Systems, ICT Competence Profile.

Table of Contents

List of Figures

List of Tables

Extended Summary (in Greek)

Α. Ορισμός Προβλήματος

Γενική περιγραφή: *Η παρούσα έρευνα τοποθετείται υπό τη γενική ερευνητική περιοχή της Λήψης Αποφάσεων με βάση Δεδομένα για τη Σχολική Ηγεσία σε τεχνολογικά-υποστηριζόμενα σχολικά περιβάλλοντα. Το γενικό Ερευνητικό Πρόβλημα αφορά σε κριτική ανάλυση και εστιασμένες προεκτάσεις (α) της υπάρχουσας εννοιολογικής περιγραφής/μοντελοποίησης και (β) των υπαρχόντων πρακτικών σχετικά με τη λήψη αποφάσεων βασισμένων σε δεδομένα στις σχολικές μονάδες, και διερευνά το πως η περιοχή της Αναλυτικής εκπαιδευτικών δεδομένων μπορεί να υποστηρίξει αυτές τις πρακτικές. Για να προσεγγίσει την επίλυση του Ερευνητικού Ερωτήματος, η έρευνα το διαιρεί σε μια σειρά από Ερευνητικές Θεματικές που συνολικά στοχεύουν να ορίσουν ή/και μοντελοποιήσουν σαφώς τις παραμέτρους του Προβλήματος ώστε να οδηγήσουν στην πρόταση νέων μεθόδων ή/και εργαλείων προς αντιμετώπισή του. Συγκεκριμένα, οι Ερευνητικές Θεματικές αναδεικνύουν και επιχειρούν να καλύψουν την ανάγκη για (α) πιο ολιστικά εννοιολογικά πλαίσια ορισμού και μοντελοποίησης των σχολικών μονάδων ως ‘πολύπλοκους’ οργανισμούς, οι οποίοι έχουν το δικό τους επίπεδο ικανότητας (ειδικότερα, ψηφιακής), (β) μια πληρέστερη κατανόηση των καθηκόντων τα οποία οι ηγέτες σχολικών μονάδων καλούνται να επιτελέσουν εντός αυτών των πολύπλοκων οργανισμών, (γ) τον τρόπο που υπάρχοντα πλαίσια και συστήματα Αναλυτικής εκπαιδευτικών δεδομένων μπορούν να υποστηρίξουν τους ηγέτες σχολικών μονάδων να επιτελέσουν αποδοτικά αυτά τα καθήκοντα, αλλά και πως αυτά τα πλαίσια και συστήματα μπορούν να ενισχυθούν για να προσφέρουν πιο ολιστική υποστήριξη και (δ) την πρόταση νέων μεθόδων με τις οποίες η Αναλυτική εκπαιδευτικών δεδομένων μπορεί να αξιοποιηθεί για να υποστηρίξει συγκεκριμένα καθήκοντα ηγετών, ήτοι να βοηθήσει τους εκπαιδευτικούς σχολείων να λάβουν πιο εστιασμένες αποφάσεις όταν σχεδιάζουν τη διδακτική πρακτική τους (π.χ., σχέδια μαθήματος ή εκπαιδευτικά σενάρια) μέσω της επιλογής εκπαιδευτικών πόρων και εργαλείων που είναι κατάλληλα για αυτούς, με βάση κριτήρια ψηφιακής ικανότητας .*

Οι Τεχνολογίες Πληροφορικής και Επικοινωνίας (ΤΠΕ) έχουν θεωρηθεί πυλωροί για τη βελτίωση της διδασκαλίας και της μάθησης στο σχολικό περιβάλλον (OECD, 2013a), συνεισφέροντας σε διάφορα επίπεδα, από το να επαυξάνουν τις εμπειρίες των μαθητών / τριών έως το να υποβοηθούν την οργανωσιακή διαχείριση των σχολικών μονάδων (OECD, 2010; European Commission, 2011). Όμως, για να λειτουργήσουν καταλυτικά και να αποδώσουν αυτά τα οφέλη, οι ΤΠΕ πρέπει να ενσωματώνονται μέσα στη δομή των σχολικών μονάδων και να μην χρησιμοποιούνται μόνον ως εργαλείο για περιστασιακές (ad hoc) λύσεις (Micheuz, 2009; European Commission, 2013a). Σε μεγάλο βαθμό, οι σχολικές μονάδες κάνουν ακόμη περιορισμένη χρήση της ευρείας κλίμακας δυνατοτήτων των ΤΠΕ για τη βελτίωση των

διδακτικών και μαθησιακών πρακτικών, καθώς και για την υποστήριξη λήψης αποφάσεων εκ μέρους της (σχολικής) ηγεσίας (European Commission, 2010; 2013; OECD, 2015a).
Οι λόγοι για αυτή την ασυνέπεια μεταξύ των δυνητικών δυνατοτήτων των ΤΠΕ και της περιορισμένης εκμετάλλευσής τους μέχρι στιγμής, είναι πολύπλευροι και πολυεπίπεδοι, δεδομένης της φύσης των ίδιων των σχολικών μονάδων ως οργανωσιακές οντότητες και πολύπλοκα συστήματα (Solar et al., 2013). Επομένως, η διαδικασία λήψης αποφάσεων από την ηγεσία όσον αφορά στην αυτο-αξιολόγηση και στην πιο αποδοτική και συστηματική χρήση ΤΠΕ πρέπει να λαμβάνει υπ' όψιν ένα ευρύ φάσμα αλληλοσχετιζόμενων παραγόντων. Οι εν λόγω παράγοντες αλληλεπιδρούν σε τρία κύρια εννοιολογικά επίπεδα της σχολικής μονάδας, ως εξής (Solar et al., 2013; Sergis & Sampson, 2016d):

- **Μικρο-επίπεδο.** Σχετίζεται με τις πρακτικές μάθησης (learning) και αξιολόγησης (assessment) που υλοποιούνται είτε μέσα στα φυσικά όρια της σχολικής μονάδας, είτε πέρα από αυτά (Mandinach, 2012; Kaufman et al., 2014; Van der Kleij et al., 2015).
- **Μεσο-επίπεδο**. Σχετίζεται με την επίβλεψη και την αξιολόγηση των διδακτικών πρακτικών και του σχεδιασμού των προγραμμάτων σπουδών της σχολικής μονάδας (Ifenthaler & Widanapathirana, 2014).
- **Μακρο-επίπεδο.** Σχετίζεται με τις διαδικασίες οργανωσιακής 'επιχειρησιακής ευφυίας' (Business Intelligence) της σχολικής μονάδας (Marsh et al., 2006; Kaufman et al., 2014).

Επομένως, οι **ηγέτες των σχολικών μονάδων** (school leaders) αναλαμβάνουν περίπλοκα καθήκοντα κατά την διαδικασία λήψης αποφάσεων, στην προσπάθειά τους να ελέγξουν και να συντονίσουν τη λειτουργία διαφορετικών σχολικών παραγόντων σε αυτά τα επίπεδα, ειδικά σε τεχνολογικά-υποστηριζόμενα περιβάλλοντα (Hauge et al., 2014). Ως απόρροια αυτού, η υποστήριξη των ηγετών κατά την συστημική εφαρμογή των ΤΠΕ στις σχολικές μονάδες, έχει χαρακτηρισθεί ως μια σημαντική πρόκληση διεθνώς (e.g., New Media Consortium, 2014; Schleicher, 2015; OECD, 2015b). Επομένως, ως πρώτο βήμα για την αντιμετώπιση της πρόκλησης, ιδιαίτερη έμφαση έχει δοθεί στην ανάγκη για μεθόδους και συστήματα μοντελοποίησης των **ψηφιακών ικανοτήτων (ICT competence)** των σχολικών μονάδων ως ολιστικών οργανισμών (e.g., Stuart et al., 2009; Vanderlinde et al., 2014; Volungeviciene et al., 2014; Kampylis et al., 2015).
Σε αυτό το πλαίσιο, η διαδικασία της ***Μοντελοποίησης Προφίλ Ψηφιακών Ικανοτήτων Σχολικών Μονάδων*** αναγνωρίζεται και προωθείται ως μία πολύ σημαντική ανάγκη διεθνώς (OECD, 2013b) τόσο σε σχέση με την 'λογοδοσία' (accountability) προς εξωτερικούς παράγοντες (πχ., γονείς, φορείς χρηματοδότησης και πολιτικής, ευρύ κοινό) (European Commission, 2015), αλλά και ως προς την εσωτερική (αυτο-)βελτίωση του σχολείου (OECD, 2015b). Αυτή η ανάγκη μπορεί να ορισθεί ως μια Ερευνητική Θεματική στο πλαίσιο του γενικού Προβλήματος της έρευνας, ως εξής:

- **Ερευνητική Θεματική #1:** Ορισμός την έννοιας της **ψηφιακής ικανότητας σχολικών μονάδων,** που να ενσωματώνει τους διάφορους παράγοντες που αλληλεπιδρούν μέσα στο περίπλοκο οικοσύστημα των σχολικών μονάδων.

Επιπλέον, οι ηγέτες σχολικών μονάδων καλούνται να συντονίσουν τον τρόπο που αυτοί οι παράγοντες δρουν εντός του περίπλοκου σχολικού οικοσυστήματος. Για να περιγραφεί αυτή η διαδικασία, έχει προταθεί η έννοια της *Λήψης Αποφάσεων Βασισμένων σε Δεδομένα* (Data-Driven Decision Making-DDDM). Η έννοια έχει οριστεί ως «η συστηματική συλλογή, ανάλυση, εξέταση και ερμηνεία δεδομένων για να ενημερωθεί η πρακτική και η πολιτική σε εκπαιδευτικά περιβάλλοντα» (Mandinach, 2012). Η DDDM αναφέρεται στην συλλογή, ανάλυση και ερμηνεία εκπαιδευτικών δεδομένων (από όλα τα επίπεδα της σχολικής μονάδας), με στόχο την υποστήριξη της ηγεσίας της σχολικής μονάδας στον συντονισμό του σχεδιασμού της γι' αυτήν, ώστε να ανταποκριθεί στις επιταγές της εξωτερικής λογοδοσίας αλλά και της εσωτερικής αυτο-αξιολόγησης και βελτίωσης (Mourshed et al. 2010; Mandinach, 2012; Dunn et al., 2013).

Λαμβάνοντας όμως υπόψη την περιπλοκότητα αυτού του συντονισμού, υπάρχει η ανάγκη να οριστούν, από μια ολιστική προσέγγιση, τα στοιχεία που τον απαρτίζουν· τα καθήκοντα δηλαδή που καλείται να επιτελέσει η σχολική ηγεσία στα διάφορα επίπεδα της σχολικής μονάδας. Αυτή η ανάγκη μπορεί να περιγραφεί ως μια δεύτερη Ερευνητική Θεματική στο πλαίσιο του γενικού Προβλήματος της έρευνας:

- **Ερευνητική Θεματική #2:** Ορισμός πλαισίου καθηκόντων της σχολικής ηγεσίας, όπου να αποτυπώνονται ολιστικά τα καθήκοντα που οι ηγέτες καλούνται να φέρουν εις πέρας στα διάφορα επίπεδα των σχολικών μονάδων.

Στο ανωτέρω πλαίσιο, έχοντας ορίσει το πλαίσιο καθηκόντων της σχολικής ηγεσίας, εγείρεται η πρόκληση της υποστήριξης των ηγετών στο να επιτελέσουν τα καθήκοντα αυτά με έναν αποτελεσματικό τρόπο. Στο γενικότερο πλαίσιο της τεχνολογικά-υποστηριζόμενης Εκπαίδευσης, μια βασική έννοια που αφορά στον πυρήνα των διαδικασιών λήψης αποφάσεων βασισμένων σε δεδομένα, είναι η **Αναλυτική Εκπαιδευτικών Δεδομένων (Analytics),** η οποία θεωρείται κομβική για την αποτελεσματική άσκηση ηγεσίας στο εκπαιδευτικό περιβάλλον σε διάφορα επίπεδα εκπαίδευσης, με μια ιδιαίτερη έμφαση στην Ανώτατη Εκπαίδευση μέχρι στιγμής (Pistilli et al., 2014). Η έννοια αφορά σε μεθόδους και εργαλεία συλλογής, επεξεργασίας και ανάλυσης εκπαιδευτικών δεδομένων από διαφορετικές πηγές, με σκοπό την υποστήριξη της λήψης αποφάσεων.

Ως αποτέλεσμα αυτού, η ερευνητική κοινότητα έχει προσπαθήσει να προτείνει και αξιοποιήσει τέτοιες μεθόδους αναλυτικής για να υποστηρίξει την λήψη αποφάσεων σε τεχνολογικά-υποστηριζόμενα σχολικά περιβάλλοντα. Για να το επιτύχει αυτό, έχει αξιοποιήσει τρεις βασικές διαστάσεις της εκπαιδευτικής αναλυτικής, οι οποίες έχουν ορισθεί στο γενικότερο πλαίσιο της τεχνολογικά-υποστηριζόμενης εκπαίδευσης, ως εξής:

- **Μαθησιακή αναλυτική (Learning Analytics).** Αναφέρεται σε μεθόδους και εργαλεία στο μικρο-επίπεδο (κυρίως) του εκπαιδευτικού οργανισμού που επιτρέπουν «την μέτρηση, συλλογή, ανάλυση και αναφορά δεδομένων για τους μαθητές / τριες και τα πλαίσιά (context) τους, με σκοπό την κατανόηση και βελτιστοποίηση της μάθησης και των πλαισίων μέσα στα οποία αυτή επισυμβαίνει» (SOLAR, 2011)
- **Διδακτική αναλυτική (Teaching Analytics).** Στόχος της είναι να παράσχει ανάλυση και αξιολόγηση των διδακτικών πρακτικών του εκπαιδευτικού οργανισμού (με έμφαση στο μεσο-επίπεδο). Κυρίως αναφέρεται σε μεθόδους και εργαλεία που επιτρέπουν στους διδάσκοντες (ή στους εκπαιδευτικούς σχεδιαστές) να αναλύσουν τους εκπαιδευτικούς σχεδιασμούς τους, ώστε να αναστοχαστούν καλύτερα πάνω σε αυτούς (είτε συνολικά ή σε επιμέρους στοιχεία τους) και να τους βελτιώσουν ώστε να προφέρουν καλύτερες εμπειρίες στους μαθητές. Επίσης, μπορεί να αφορά και στην ανάλυση και αξιολόγηση προγραμμάτων σπουδών του εκπαιδευτικού οργανισμού.
- **Ακαδημαϊκή αναλυτική (Academic Analytics).** Στοχεύει να παράσχει υποστήριξη στη λήψη αποφάσεων με βάση δεδομένα στα μεσο / μακρο επίπεδα που σχετίζονται κυρίως με την οργανωσιακή ευφυία (Business Intelligence) του εκπαιδευτικού οργανισμού (Ferreira & Andrade, 2016).

Όπως προαναφέρθηκε, η Αναλυτική δεδομένων μέχρι στιγμής έχει εστιάσει ιδιαίτερα στην Ανώτατη Εκπαίδευση, παρ' όλο που δυνητικά αφορά σε όλα τα εκπαιδευτικά επίπεδα. Ως αποτέλεσμα αυτής της τάσης, όσον αφορά στις σχολικές μονάδες ('K-12' εκπαίδευση), οι προαναφερθείσες διαστάσεις της αναλυτικής δεν μπορούν να υποστηρίξουν πλήρως το έργο της σχολικής ηγεσίας. Αυτή η υπόθεση βασίζεται στο γεγονός ότι οι ηγέτες των K-12 σχολείων απαιτούν ολιστική υποστήριξη στη λήψη αποφάσεων βάσει δεδομένων, ώστε να εμπλακούν αποτελεσματικά στο περίπλοκο έργο τους, με δεδομένη την οικοσυστημική φύση των σχολείων (OECD, 2013c). Ειδικότερα, αυτό το έργο απαιτεί συλλογή και επεξεργασία δεδομένων από όλα τα επίπεδα της σχολικής μονάδας, ώστε να παρθούν αποφάσεις για την συστημική ανάπτυξη του σχολείου, η οποία εκτείνεται σε ευρύ φάσμα· από την παρακολούθηση, υποστήριξη και βελτίωση των επιδόσεων και εμπειριών κάθε μαθητή στο μικρο-επίπεδο έως το σχεδιασμό και υλοποίηση στρατηγικών πλάνων για το σχολείο ως οργανισμό. Επίσης, ένα επιπλέον πρόβλημα αφορά στο ότι τα υπάρχοντα συστήματα υποστήριξης αποφάσεων (decision support systems) που έχουν προταθεί για να προσφέρουν υπηρεσίες Αναλυτικής ώστε να υποστηρίξουν τη σχολική ηγεσία δεν έχουν φθάσει στο επίπεδο ωριμότητας (από πλευράς λειτουργιών) ώστε να υποστηρίξουν πλήρως όλο το φάσμα των έργων που επιτελεί η σχολική ηγεσία (Kaufman et al., 2014).

Με βάση τα παραπάνω, οι υπάρχουσες κατηγορίες εκπαιδευτικής αναλυτικής δεδομένων δεν υποστηρίζουν πλήρως και ολιστικά τη διαδικασία λήψης αποφάσεων που απαιτείται από την ηγεσία των K-12 σχολείων. Επομένως, γίνεται φανερή η ανάγκη να προταθεί ένα πλαίσιο που να υποστηρίζει ολιστική πολυεπίπεδη «*Σχολική Αναλυτική*», που να ενσωματώνει και να αναλύει δεδομένα από τα διάφορα επίπεδα της σχολικής μονάδας με έναν συνεκτικό τρόπο. Αυτή η ανάγκη μπορεί να ορισθεί ως μια Ερευνητική Θεματική στο πλαίσιο του γενικού Προβλήματος της έρευνας:

– **Ερευνητική Θεματική #3:** Ορισμός ενός πλαισίου ολιστικής «*Σχολικής Αναλυτικής*» για την υποστήριξη της ηγεσίας σχολικών μονάδων χρησιμοποιώντας εκπαιδευτικά δεδομένα προερχόμενα από όλα τα επίπεδα των σχολικών μονάδων.

Όπως προαναφέρθηκε, τα υπάρχοντα υποστηρικτικά συστήματα (decision support systems) δεν έχουν φθάσει στο επίπεδο ωριμότητας (από πλευράς λειτουργιών) ώστε να υποστηρίξουν πλήρως όλο το φάσμα των έργων που επιτελεί η σχολική ηγεσία (Sergis & Sampson, 2016a). Πιο συγκεκριμένα, η εστίαση των υπαρχόντων συστημάτων υποστήριξης της λήψης αποφάσεων των ηγετών των K-12 σχολείων αφορούσε πρωταρχικά στην υποστήριξη των καθηκόντων που αφορούν στην εξωτερική λογοδοσία των σχολικών μονάδων και την αξιολόγησή τους. Έτσι, οι κεντρικοί στόχοι τέτοιων συστημάτων φάνηκε να επικεντρώνονται στο να παρέχουν μια ποσοτική θεώρηση συγκεκριμένων οργανωσιακών διαδικασιών των σχολείων, οι οποίες συνήθως χρησιμοποιούνται ως βάση για την εξωτερική λογοδοσία. Όμως λιγότερη προσοχή έχει δοθεί στο να παρασχεθούν στοχευμένες συστάσεις στην ηγεσία (ειδικά και σε εκπαιδευτικούς) για το πώς θα βελτιώσουν την ικανότητά τους και συνεισφορά τους στην εσωτερική και αειφόρα σχολική βελτίωση. Ένα χαρακτηριστικό παράδειγμα τέτοιων διαδικασιών λήψης αποφάσεων είναι η υποστήριξη των εκπαιδευτικών να σχεδιάζουν αποτελεσματικά τον εκπαιδευτικό σχεδιασμό τους με χρήση ψηφιακών πόρων, λαμβάνοντας υπ' όψιν το προφίλ ψηφιακών ικανοτήτων τους (Mandinach & Gummer, 2015). Επομένως, υπάρχει ανάγκη για περαιτέρω έρευνα σε αυτήν την περιοχή, η οποία να εστιάσει στο σχεδιασμό και υλοποίηση μεθόδων και συστημάτων για να υποστηριχθούν οι εκπαιδευτικοί κατά τη διάρκεια τέτοιων διαδικασιών. Σε αυτό το πλαίσιο, βασικά παραδείγματα συστημάτων υποστήριξης λήψης τέτοιων αποφάσεων είναι τα **Συστήματα Συστάσεων** (recommender systems (RS)).

Τα Συστήματα Συστάσεων (Recommender Systems - RS) είναι εργαλεία λογισμικού σχεδιασμένα να βοηθούν τους χρήστες να διαχειρίζονται το πρόβλημα της υπερφόρτωσης πληροφοριών, με το να εντοπίζουν και επισημαίνουν τις πλέον κάταλληλες πληροφορίες με έναν προσωποποιημένο τρόπο (Bobadilla et al., 2013; Manouselis et al., 2013; Drachsler, 2015). Έχουν χρησιμοποιηθεί σε μια ευρεία κλίμακα περιβαλλόντων εφαρμογής, όπως στο ηλεκτρονικό εμπόριο (Huang et al., 2007) και στην τεχνολογικά υποστηριζόμενης μάθηση (technology enhanced learning -TeL) Manouselis et al., 2013). Στο περιβάλλον της TeL, τα Συστήματα Συστάσεων έχουν κυρίως χρησιμοποιηθεί για τη σύσταση Μαθησιακών Αντικειμένων, τα οποία να ανταποκρίνονται στα προφίλ συγκεκριμένων εκπαιδευτικών και μαθητών /τριών (Manouselis et al., 2013). Όμως, παρόλο που η έρευνα πάνω σε μεθόδους συστάσεων για μαθητές/τριες έχει απασχολήσει τους ερευνητές σε ευρεία κλίμακα, οι εκπαιδευτικοί δεν έχουν γίνει αντικείμενο ανάλογης ερευνητικής προσοχής. Επιπλέον, η σχετική έρευνα με έμφαση την υποστήριξη των εκπαιδευτικών υπολείπεται και ως προς τις μεθόδους *δημιουργίας προφίλ* ώστε να καταγραφούν και να χρησιμοποιηθούν καταλλήλως τα προσωπικά τους χαρακτηριστικά (όπως η ψηφιακή τους ικανότητα), για να τους παρασχεθούν τελικά εξατομικευμένες προτάσεις (Dyckhoff et al., 2013).

Λαμβάνοντας υπ' όψιν τον σημαντικό ρόλο των εκπαιδευτικών στην υιοθέτηση διδακτικών / εκπαιδευτικών καινοτομιών υποστηριζόμενων από την τεχνολογία σε σχολικό επίπεδο (Goktas et al., 2013), την πολυπλοκότητα της διδακτικής πρακτικής που υποστηρίζεται από την τεχνολογία (Solar et al., 2013) και την σημερινή ποικιλότητα της ψηφιακής ικανότητας του κάθε εκπαιδευτικού (Sang et al., 2010; Vanderlinde et al., 2014), είναι εμφανές ότι οι ψηφιακές ικανότητες των εκπαιδευτικών συνιστούν ένα σημαντικό στοιχείο που μπορεί δυνητικά να επηρεάσει την δυνατότητα τους να εμπλακούν αποτελεσματικά στις διδακτικές διαδικασίες τους σε μικρο/μεσο επίπεδο, ειδικά στο σχεδιασμό και στην διδασκαλία, με την χρήση ψηφιακών πηγών και εργαλείων. Άρα, αναδεικνύεται μια ανάγκη για το σχεδιασμό, υλοποίηση και αξιολόγηση συστημάτων υποστήριξης λήψης αποφάσεων (π.χ. συστήματα συστάσεων), προκειμένου να υποβοηθηθούν οι εκπαιδευτικοί κατά τη διάρκεια του σχεδιασμού (και παράδοσης) της διδακτικής τους πρακτικής με την χρήση ΤΠΕ πόρων και εργαλείων, λαμβάνοντας υπ' όψιν τους τις ψηφιακές ικανότητες των εκπαιδευτικών. Αυτή η ανάγκη μπορεί να ορισθεί ως μια Ερευνητική Θεματική στο πλαίσιο του γενικού Προβλήματος της έρευνας:

- **Ερευνητική Θεματική #4:** Σχεδιασμός, υλοποίηση και αξιολόγηση συστημάτων συστάσεων που απευθύνονται σε εκπαιδευτικούς, για την υποστήριξη του σχεδιασμού της διδακτικής τους πρακτικής με χρήση ψηφιακών πόρων και εργαλείων λαμβάνοντας υπ 'όψιν το προφίλ ψηφιακών τους ικανοτήτων.

Σε αυτό το πλαίσιο, η παρούσα διδακτορική διατριβή στοχεύει να διερευνήσει τα τέσσερα διαπιστωθέντα Ερευνητικά Προβλήματα και να διευρύνει την παρούσα επιστημονική συζήτηση (state of the art) στις σχετιζόμενες ερευνητικές περιοχές, μέσω τεσσάρων διασυνδεδεμένων περιοχών συνεισφοράς, ως εξής:

1. **Συνεισφορά #1:** Πρόταση πλαισίου για την δημιουργία προφίλ των ψηφιακών ικανοτήτων των σχολικών μονάδων ως περίπλοκες οργανωσιακές οντότητες (**Ερευνητική Θεματική #1**).
2. **Συνεισφορά #2:** Πρόταση πλαισίου για την υποστήριξη ολιστικής ηγεσίας βασισμένης σε δεδομένα (**Ερευνητική Θεματική #2**).
3. **Συνεισφορά #3:** Πρόταση πλαισίου Σχολικής Αναλυτικής για την υποστήριξη της σχολικής ηγεσίας στην εφαρμογή ολιστικής λήψης αποφάσεων βασισμένης σε δεδομένα (**Ερευνητική Θεματική #3**).

4. **Συνεισφορά #4:** Σχεδίαση, εφαρμογή και αξιολόγηση Συστημάτων Συστάσεων (RS) για να διευκολυνθούν οι εκπαιδευτικοί να εμπλακούν αποτελεσματικότερα στο σχεδιασμό και παράδοση της διδασκαλίας τους, μέσω της επιλογής κατάλληλων μαθησιακών αντικειμένων, βασισμένων στα ατομικά προφίλ ψηφιακών ικανοτήτων τους (**Ερευνητική Θεματική #4**).

Β. Περιγραφή Αποτελεσμάτων Έρευνας

Στην παρούσα ενότητα παρουσιάζουμε την συνεισφορά της διατριβής στην αντιμετώπιση των Ερευνητικών Θεματικών που ετέθησαν στην προηγούμενη ενότητα.

Συνεισφορά #1: Πρόταση πλαισίου για την δημιουργία προφίλ των ψηφιακών ικανοτήτων των σχολικών μονάδων ως περίπλοκες οργανωσιακές οντότητες

Η συνεισφορά της παρούσας Διδακτορικής Διατριβής σχετίζεται με την εισαγωγή της έννοιας της **Ψηφιακής Ικανότητας της Σχολικής Μονάδας** από μία οργανωσιακή οπτική και την πρόταση για ένα **Πλαίσιο Δημιουργίας Προφίλ Ψηφιακών Ικανοτήτων Σχολικών Μονάδων** για την μοντελοποίηση των διαφόρων διαστάσεων αυτής της έννοιας ([**P5**], [**P8**]). Εκτός αυτού, σχεδιάστηκε και **ένα σύστημα διαχείρισης των Ψηφιακών Ικανοτήτων των Σχολικών Μονάδων** ([**P2**]).

Το προτεινόμενο πλαίσιο δομείται επί υπαρχουσών προσεγγίσεων για την καταγραφή του επιπέδου αξιοποίησης ΤΠΕ της σχολικής μονάδας, δηλαδή της έννοιας της **η-Ωριμότητας (eMaturity)** (Durando et al., 2007; Solar et al., 2013). Επιπλέον, υποστηρίζεται ότι είναι απαραίτητη μία διεύρυνση αυτών των προσεγγίσεων προς την κατεύθυνση της πληρέστερης αποτύπωσης των ψηφιακών ικανοτήτων του εκπαιδευτικού προσωπικού του σχολείου (π.χ. εκπαιδευτικοί και διευθυντές), κάτι που δεν προβλεπόταν σαφώς στις προσεγγίσεις η-Ωριμότητας. Η αιτιολόγηση για αυτήν την διεύρυνση ήταν το ότι αυτοί οι παράγοντες της σχολικής μονάδας παίζουν ένα σημαντικό ρόλο στον συνολικό σχεδιασμό και στην απόδοση της στρατηγικής της σχολικής μονάδας ως προς τις ΤΠΕ. Άρα, οι ειδικές ψηφιακές ικανότητές τους πρέπει να ληφθούν ρητά υπ’ όψιν κατά τη μέτρηση του επιπέδου της Ψηφιακής Ικανότητας της Σχολικής Μονάδας. Με την προσθήκη κατάλληλων πλαισίων καταγραφής των προφίλ των ψηφιακών ικανοτήτων των παραγόντων της οικοσυστημικής δομής τους, οι σχολικές μονάδες μπορούν να ελέγξουν όχι μόνον τις διαδικασίες στις οποίες αυτά εμπλέκονται αλλά και το επίπεδο της ατομικής τους ικανότητας να τις φέρουν εις πέρας. Η σημαντικότερη προστιθέμενη αξία είναι ότι παρέχεται μια πιο λεπτομερής καταγραφή των ικανοτήτων των κάθε παραγόντων της σχολικής μονάδας. Επομένως είναι δυνατόν να εντοπιστούν με μεγαλύτερη ακρίβεια οι αιτίες τυχόν χαμηλής ικανότητας/επίδοσης σε λειτουργικές περιοχές της σχολικής μονάδας, και να συνδεθούν με τις συγκεκριμένες ψηφιακές ικανότητες των μελών που συν-επιτελούν τις εκάστοτε λειτουργίες· επιτρέποντας στοχευμένες ενέργειες βελτίωσης.

Επιπλέον, με βάση το προαναφερθέν εννοιολογικό μοντέλο της ψηφιακής ικανότητας της σχολικής μονάδας, σχεδιάστηκε ένα αρχικό **σύστημα διαχείρισης της Ψηφιακής Ικανότητας της σχολικής μονάδας** ([**P2**]. Αυτό το σύστημα δομήθηκε με βάση τις διαστάσεις του ορισθέντος πλαισίου της ψηφιακής ικανότητας της σχολικής μονάδας. Το σύστημα διαχείρισης της ψηφιακής ικανότητας της σχολικής μονάδας προτάθηκε ως ένα πιθανό μέσο θεώρησης και της διατήρησης του οράματος των σχολικών μονάδων όσον αφορά στην χρήση ΤΠΕ. Το προτεινόμενο σύστημα στοχεύει να παράσχει λειτουργικές διευκολύνσεις για την λήψη αποφάσεων στους εκπαιδευτικούς και στην ηγεσία όσον αφορά στην καταγραφή, τον έλεγχο και την ενημέρωση των ψηφιακών ικανοτήτων των εκπαιδευτικών ατομικά και της σχολικής μονάδας ως οργανισμού.

Τα αποτελέσματα αυτής της έρευνας έχουν δημοσιευθεί σε επιστημονικά περιοδικά, βιβλία και διεθνή συνέδρια ως ακολούθως:

- **[P2]** Sergis, S., Zervas, P., & Sampson, D. (2014). A holistic approach for managing School ICT Competence Profiles towards supporting school ICT uptake. *International Journal of Digital Literacy and Digital Competence, 5*(4), 2014.
- **[P5]** Sergis, S., & Sampson, D. (2014). From Teachers' to Schools' ICT Competence Profiles, In D. Sampson, D. Ifenthaler, J. M. Spector , & P. Isaias, (Eds.), *Digital Systems for Open Access to Formal and Informal Learning* (pp. 307-327). International Publishing: Springer.
- **[P7]** Sergis, S., Sholla, I., Zervas, P., & Sampson, D. (2014). Supporting School ICT Uptake: The ASK School ICT Competence Management System. In *Proc. of the International Conference on Interactive Mobile and Computer Aided Learning 2014* (pp. 359 – 363), Thessaloniki: IEEE.
- **[P8]** Sergis S., & Sampson, D. (2014). Towards a School ICT Competence Profiling Framework. In *Proc. of the 14th IEEE International Conference on Advanced Learning Technologies (ICALT 2014)* (pp. 759 – 761), Athens: IEEE.

Συνεισφορά #2: Πρόταση πλαισίου για την υποστήριξη ολιστικής ηγεσίας βασισμένης σε δεδομένα

Η κύρια συνεισφορά της διατριβής σε αυτήν την περιοχή είναι η πρόταση ενός ολιστικού πλαισίου καταγραφής των βασικών καθηκόντων της ηγεσίας των σχολικών μονάδων και των απαιτούμενων δεδομένων που να προέρχονται από όλον τον οργανισμό, ώστε αυτά τα καθήκοντα να εκτελεσθούν αποτελεσματικά. Επιπλέον, η έρευνα στόχευε να ορίσει τα ηγετικά καθήκοντα που υποστηρίζονται με ψηφιακά εργαλεία και θα μπορούσαν επομένως να επωφεληθούν από περαιτέρω έρευνα στα συστήματα που υποστηρίζουν την λήψη αποφάσεων ενσωματώνοντας την έννοια της (σχολικής) ψηφιακής ικανότητας.

Στην πορεία προς την διαμόρφωση του λεπτομερούς πλαισίου των κεντρικών καθηκόντων της ηγεσίας των σχολικών μονάδων, κρίθηκε σημαντικό να μελετηθούν οι υπάρχουσες προσεγγίσεις που αφορούν στα ηγετικά καθήκοντα στο σχολικό περιβάλλον. Τα αποτελέσματα αυτής της διερεύνησης ήταν τα ακόλουθα:

- η διαμόρφωση ενός Πλαισίου κεντρικών καθηκόντων της σχολικής ηγεσίας που απεικονίζει ένα σύνολο συχνά αναφερόμενων καθηκόντων της ηγεσίας σε όλα τα σχολικά επίπεδα.
- μια κριτική ανάλυση των υπαρχόντων συστημάτων υποστήριξης της λήψης αποφάσεων με βάση δεδομένα όσον αφορά στην ικανότητά τους να υποστηρίξουν πλήρως το προαναφερθέν πλαίσιο.

Τα αποτελέσματα αυτής της έρευνας έχουν δημοσιευθεί στο ακόλουθο κεφάλαιο επιστημονικού βιβλίου:

- **[P4]** Sergis, S., & Sampson, D.G. (2016). Data Driven Decision Support For School Leadership: Analysis Of Supporting Systems. In J. M. Spector, D. Ifenthaler, D. Sampson, & P. Isaias (Eds.), *ICT in education in global context: Comparative Reports of Innovations in K-12 Education* (pp. 145-171), Berlin Heidelberg: Springer.

Συνεισφορά #3: Πρόταση πλαισίου Σχολικής Αναλυτικής για την υποστήριξη της σχολικής ηγεσίας στην εφαρμογή ολιστικής λήψης αποφάσεων βασισμένης σε δεδομένα

Η κύρια συνεισφορά της διατριβής σε αυτήν την επιστημονική περιοχή είναι το ότι ορμώμενη από τα αποτελέσματα της συνεισφοράς #2 προτείνει ένα νέο πεδίο Αναλυτικής, συγκεκριμένα την *Σχολική Αναλυτική,* η οποία υπερβαίνει τους περιορισμούς της Διδακτικής / Μαθησιακής και Ακαδημαϊκής Αναλυτικής όσον αφορά στα κεντρικά σημεία και τους στόχους της και εστιάζει καθαρά στο πλαίσιο της σχολικής μονάδας. Ειδικότερα, η διατριβή ανέλυσε με κριτικό τρόπο τις υπάρχουσες αναλυτικές κατευθύνσεις όσον αφορά στην ικανότητά τους να παρέχουν ολιστική υποστήριξη λήψης αποφάσεων που απαιτείται από την ηγεσία των σχολικών μονάδων, π.χ. συνδέοντας δεδομένα «business intelligence» (μακρο-επίπεδο) και διδακτικά / μαθησιακά (μικρο – και μεσο- επίπεδο) δεδομένα. Με βάση τα πορίσματα αυτής της ανάλυσης, ένα νέο ολιστικό πολυεπίπεδο πλαίσιο Σχολικής Αναλυτικής προτάθηκε με στόχο να ενσωματώσει δεδομένα από όλα τα σχολικά επίπεδα. Επιπλέον, το πλαίσιο Σχολικής Αναλυτικής αρχικά πρότεινε μια μέθοδο σύνδεσης των καθηκόντων της σχολικής ηγεσίας (βλ. Συνεισφορά #2) με δεδομένα από ολόκληρη την σχολική μονάδα, ούτως ώστε να ενημερώσει τον ολιστικό στρατηγικό σχεδιασμό της σχολικής μονάδας.

Τα αποτελέσματα αυτής της έρευνας δημοσιεύτηκαν στο ακόλουθο κεφάλαιο επιστημονικού βιβλίου:

- **[P3]** Sergis, S., & Sampson, D. (2016). School Analytics: A Framework for Supporting Systemic School Leadership. In J. M. Spector, D. Ifenthaler, D. Sampson, & P. Isaias (Eds.), *Competencies in Teaching, Learning and Educational Leadership in the Digital Age* (pp. 79-122), Springer

Συνεισφορά #4: Σύστημα Συστάσεων Μαθησιακών Αντικειμένων σε Εκπαιδευτικούς με βάση το προφίλ των ψηφιακών ικανοτήτων τους

Η κύρια συμβολή της διατριβής σε αυτήν την επιστημονική περιοχή αφορά στα μικρο/μεσο-επίπεδα της οργάνωσης, εξετάζοντας την δυνατότητα των Συστημάτων Συστάσεων (Recommender Systems (RS)) να παράσχουν υποστήριξη στη λήψη αποφάσεων των εκπαιδευτικών· συγκεκριμένα, όσον αφορά σε αποτελεσματικές και εξατομικευμένες προτάσεις για Μαθησιακά Αντικείμενα για τον διδακτικό τους σχεδιασμό και παράδοση, με την καινοτομία της προσέγγισης να έγκειται στο ότι εκμεταλλεύεται το προφίλ των ψηφιακών ικανοτήτων τους.

Ειδικότερα, η συνεισφορά της διατριβής στην παραπάνω επιστημονική περιοχή σχετίζεται ιδίως με:

- την αξιολόγηση της προστιθέμενης αξίας της ενσωμάτωσης **των ψηφιακών ικανοτήτων των εκπαιδευτικών** σε ένα σύστημα συστάσεων (RS) Μαθησιακών Αντικειμένων
- τον σχεδιασμό και την αξιολόγηση ενός μηχανισμού για την δυναμική εκμαίευση (elicitation) των ψηφιακών ικανοτήτων των εκπαιδευτικών
- τον σχεδιασμό και την αξιολόγηση ενός διευρυμένου συστήματος συστάσεων (recommender system) μαθησιακών αντικειμένων, το οποίο εκμαιεύει δυναμικά τα προφίλ των ψηφιακών ικανοτήτων των εκπαιδευτικών και τα χρησιμοποιεί για να παρέχει συστάσεις για μαθησιακά αντικείμενα με βάση τις ψηφιακές τους ικανότητες.

Τα αποτελέσματα αυτής της έρευνας έχουν δημοσιευθεί σε επιστημονικό περιοδικό και διεθνή συνέδρια ως ακολούθως:

- **[P1]** Sergis, S., & Sampson, D. (2016). Learning Object Recommendations For Teachers Based On Elicited ICT Competence Profiles. *IEEE Transactions on Learning Technologies, 9*(1), 67-80.
- **[P6]** Sergis, S., & Sampson, D. (2015). Enhancing Learning Object Recommendations for Teachers Using Adaptive Neighbor Selection. In *Proceedings of the 15th IEEE International Conference on Advanced Learning Technologies (ICALT 2015)* (pp. 391-393). Hualien: IEEE.

- **[P9]** Sergis, S., Zervas, P., & Sampson, D. (2014). Towards Learning Object Recommendations based on Teachers' ICT Competence Profiles. In *Proceedings of the 14th IEEE International Conference on Advanced Learning Technologies (ICALT 2014)* (pp. 534 – 538), Athens: IEEE
- **[P10]** Sergis, S., Zervas, P., & Sampson, D. (2014). ICT Competence-based Learning Object Recommendations for Teachers. In *Proceedings of the IADIS 11th International Conference on Cognition and Exploratory Learning in Digital Age (CELDA2014)* (pp. 150-157). Porto: IADIS.
- [P11] Sergis, S., & Sampson, D. (2014). Eliciting Teachers' ICT Competence Profiles Based on Usage Patterns within Learning Object Repositories. In *Proceedings of the 6th IEEE International Conference on Technology in Education 2014 (IEEE T4E2014)* (pp. 99 - 105), Amrita: IEEE.

Publications based on this Thesis

- **Two (2) International Journal Papers**: Two (2) papers published.
- **Three (3) Book Chapters**: Three (3) book chapters published.
- **Six (6) International Conference Papers**: Six (6) papers presented and published in the proceedings of International Conferences.

International Journals

[P1] Sergis, S., & Sampson, D. (2016). Learning Object recommendations for teachers based on elicited ict competence profiles. *IEEE Transactions on Learning Technologies, 9*(1), 67-80.

[P2] Sergis, S., Zervas, P., & Sampson, D. (2014). A holistic approach for managing School ICT Competence Profiles towards supporting school ICT uptake. *International Journal of Digital Literacy and Digital Competence, 5*(4), 2014.

Book Chapters

[P3] Sergis, S., & Sampson, D. (2016). School analytics: A framework for supporting systemic school leadership. In J. M. Spector, D. Ifenthaler, D. Sampson, & P. Isaias (Eds.), *Competencies in Teaching, Learning and Educational Leadership in the Digital Age* (pp. 79-122), Springer.

[P4] Sergis, S., & Sampson, D.G. (2016). Data driven decision support for school leadership: analysis of supporting systems. In J. M. Spector, D. Ifenthaler, D. Sampson, & P. Isaias (Eds.), *ICT in education in global context: Comparative Reports of Innovations in K-12 Education* (pp. 145-171), Berlin Heidelberg: Springer.

[P5] Sergis, S., & Sampson, D. (2014). From Teachers' to schools' ict competence profiles. In D. Sampson, D. Ifenthaler, J. M. Spector, & P. Isaias, (Eds.), *Digital Systems for Open Access to Formal and Informal Learning* (pp. 307-327). International Publishing: Springer.

International Conferences

[P6] Sergis, S., & Sampson, D. (2015). Enhancing learning object recommendations for teachers using adaptive neighbor selection. In *Proc. of the 15th IEEE International Conference on Advanced Learning Technologies (ICALT 2015)* (pp. 391-393). Hualien: IEEE.

[P7] Sergis, S., Sholla, I., Zervas, P., & Sampson, D. (2014). Supporting school ict uptake: The ASK school ict competence management system. In *Proc. of the International Conference on Interactive Mobile and Computer Aided Learning 2014* (pp. 359 – 363), Thessaloniki: IEEE.

[P8] Sergis S., & Sampson, D. (2014). Towards a School ict competence profiling framework. In *Proc. of the 14th IEEE International Conference on Advanced Learning Technologies (ICALT 2014)* (pp. 759 – 761), Athens: IEEE.

[P9] Sergis, S., Zervas, P., & Sampson, D. (2014). Towards learning object recommendations based on teachers' ICT competence profiles. In *Proc. of the 14th IEEE International Conference on Advanced Learning Technologies (ICALT 2014)* (pp. 534 – 538), Athens: IEEE.

[P10] Sergis, S., Zervas, P., & Sampson, D. (2014). ICT competence-based learning object recommendations for teachers. In *Proc. of the IADIS 11th International Conference on Cognition and Exploratory Learning in Digital Age (CELDA2014)* (pp. 150-157). Porto: IADIS.

[P11] Sergis, S., & Sampson, D. (2014). Eliciting teachers' ICT competence profiles based on usage patterns within learning object repositories. In *Proc. of the 6th IEEE International Conference on Technology in Education 2014 (IEEE T4E2014)* (pp. 99 - 105*)*, Amrita: IEEE.

1 Introduction

1.1 Motivation and Problem Statement

Overall Outline: *This work is placed within the overarching research field of data-driven decision making for school leadership within ICT-supported school environments. The main Research Problem relates to providing a critical analysis and targeted enhancements of (a) the conceptualization / modelling and (b) existing practices, of data-driven decision making in schools and how educational data analytics methods and tools can support such practices. To approach the Research Problem, this work divided it in a set of Research Areas, which aim to define and/or model each parameter of the Problem, so as to propose methods and/or tools to address it. More specifically, this work stresses and attempts to address the need for (a) more holistic frameworks to conceptualize and model schools as 'complex' organizations having their own level of competence and hosting an ecosystem of inter-relating actors, (b) a better understanding of the specific tasks that school leaders are expected to perform within these complex ecosystems, (c) how educational data Analytics methods and tools can scaffold school leaders to effectively engage in these tasks and how these methods and tools could be enhanced to provide more holistic support and (d) introducing novel ways that data Analytics decision-support methods can be utilized to facilitate specific school leadership tasks, i.e., help school teachers to make more informed decisions when creating their teaching designs (e.g., lesson plans or educational scenarios) by selecting resources and tools based on competence-related criteria.*

Information and Communication Technologies (ICT) have been repeatedly celebrated as a harbinger of teaching and learning enhancement in the context of schools (OECD, 2013a), spanning from enhancing students' learning experiences to facilitating organizational management (OECD, 2010; European Commission, 2011). In order to reap these benefits and provide a driver for change, however, ICT needs to be incorporated into the fabric of schools, and not just be used as a tool for ad-hoc solutions (Micheuz, 2009; European Commission, 2013a). Evidence shows that schools have shown limited exploitation of the full range of ICT potential as an enabler of improved learning and teaching practices as well as leadership decision making (European Commission, 2010; 2013; OECD, 2015a).

The reasons for this are multi-faceted and multilevel, bearing in mind that schools are, themselves, organizational entities comprising complex systems (Solar et al., 2013). Therefore, the leadership decision making processes for informing school self-evaluation and improvement using ICT are highly complex and need to take into account a wide range of interrelating factors. These factors interplay on three main conceptual school institutional layers, as follows (Solar, 2013; Sergis & Sampson, 2016d):

- **micro layer**, which is primarily related to the learning and assessment practices occurring either within the physical educational organization premises or beyond them (Mandinach, 2012; Kaufman et al., 2014; Van der Kleij et al., 2015).
- **meso layer**, which is primarily related to monitoring and evaluating the teaching practices and curriculum planning of the school (Ifenthaler & Widanapathirana, 2014).
- **macro layer**, which is primarily related to the organizational 'business intelligence' development processes of the school (Marsh et al., 2006; Kaufman et al., 2014).

Within and across these layers, **school leaders** face complex decision making tasks in their efforts to monitor and orchestrate the performance of different school actors, e.g., among others, students, teachers, parents, school equipment (Hauge et al., 2014). Spanning from this, supporting school leaders in *driving systemic ICT uptake* in schools has been reported as a significant challenge (e.g., New Media Consortium, 2014; Schleicher, 2015; OECD, 2015b) with a specific focus on the need for methods and systems for modelling the **ICT competence** profiles of the school leaders and teachers, as well as of the schools as holistic organizations (e.g., Stuart et al., 2009; Vanderlinde et al., 2014; Volungeviciene et al., 2014; Kampylis et al., 2015).

In this context, the process of ***school ICT competence profiling*** is identified and promoted as a very significant need globally (OECD, 2013b), both in terms of external accountability (European Commission, 2015), as well as for using ICT to drive internal school improvement (OECD, 2015b). This need can be defined as a Research Area of the overarching Research Problem, as follows:

- **Research Area #1:** Define a conceptualization of the concept of **school ICT competence** encapsulating the diverse school actors interplaying within the school complex ecosystem.

Additionally, school leaders are expected to orchestrate how these actors act within the complex school ecosystem. To describe this cumbersome task, the concept of Data-Driven Decision Making (DDDM) has emerged as "the systematic collection, analysis, examination, and interpretation of data to inform practice and policy in educational settings" (Mandinach, 2012). DDDM refers to the collection, analysis, and interpretation of educational data (from all layers) in order to support leaders to orchestrate their schools' planning towards meeting external accountability mandates as well as driving internal self-evaluation and improvement (Mourshed et al. 2010; Mandinach, 2012; Dunn et al., 2013).

Considering the complexity of this orchestration, however, there is a need to holistically conceptualize and describe the specific elements that constitute it, namely the tasks that school leaders perform across the different layers of the school. This need can be defined as a Research Area of the overarching Research Problem, as follows:

- **Research Area #2:** Define a School Leadership Task framework to holistically depict the leadership tasks that K12 school leaders perform across the different school layers.

Having defined a framework to inform the core school leadership tasks, another challenge relates to supporting school leaders to engage with these tasks. In the general context of technology-supported Education, a response to this challenge (support data-driven decision making of educational organizations), is the concept of (educational) **Data Analytics**, which is considered essential for effective educational leadership, yet mainly focusing on Higher Education (Pistilli et al., 2014). This concept refers to methods and tools to collect and analyze educational data from diverse sources, so as to inform decision making. As a result, the research community has been striving towards identifying effective educational analytics methods for supporting school leadership decision making, capitalizing on the three main Analytics strands proposed in the general context of technology-supported Education:

- **Learning Analytics**, which refers to methods and tools that allow "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (SOLAR, 2011)
- **Teaching Analytics**, which aim to provide analysis and evaluation of the teaching practices of an educational organization. More commonly, they refer to methods and tools that enable teachers (or instructional designers) to analyse their designs in order to better reflect on them (as a whole or elements of them). Also, it can refer to the analysis and evaluation of the curriculum.
- **Academic Analytics**, which aim at providing data-driven decision support on a meso/macro layers related to the Business Intelligence of the educational institution (Ferreira & Andrade, 2016).

As aforementioned, even though Data Analytics is relevant to all educational levels (K-12, HEI, VET etc), when the focus of study is narrowed down to K-12 schools, the aforementioned analytics strands do not adequately support the tasks of K-12 school leadership. This standpoint is based on the fact that K-12 school leaders require holistic data driven decision support in order to effectively engage with their complex tasks, given the ecosystemic nature of schools (OECD, 2013c). More specifically, these tasks require highly granulated data collection and processing from all school layers towards actionable decisions for systemic school development; spanning from monitoring, scaffolding and improving the performance and learning experiences of individual students to the strategic planning of the school as an organization. Lastly, an additional issue relates to the fact that existing decision support systems have not yet reached their full potential to support the full spectrum of school leaders' tasks (Kaufman et al., 2014).

Under the light of the above, it becomes evident that the existing analytics strands do not offer the capacity for the holistic decision support required by K-12 school leaders, i.e., for combining "business intelligence" (macro-layer) data and teaching/learning (micro- and meso-layer) data. Therefore, a need is identified for proposing a holistic multi-level "*School Analytics"* framework aiming to integrate and analyze data across school layers, in an intertwining manner.

This need can be defined as a Research Area of the overarching Research Problem, as follows:

- **Research Area #3:** Define a holistic "*School Analytics"* framework to support the tasks of K12 school leaders using educational data generated across all layers of the school

As aforementioned, existing decision support systems have not yet reached their full potential to support the full spectrum of school leaders' tasks (Sergis & Sampson, 2016a). More specifically, an analysis of the state-of-the-art in such systems for supporting leadership decision making process highlighted a key shortcoming in relation to their focus, namely that they were primarily set to support the tasks related to external school accountability metrics and evaluations. Thus, the core aims of such systems were shown to be mainly addressed at providing a quantitative overview of specific organizational processes of schools, which are commonly used as a basis of meeting external accountability mandates.

However, less attention has been placed on providing targeted recommendations to leaders (especially teachers) towards enhancing their capacity to engage in tasks related to (internally-led) sustainable school improvement. A key example of such decision-making processes is the facilitation of school teachers to engage in effective teaching practice design and delivery using ICT resources, by considering their ICT competence profiles (Mandinach & Gummer, 2015). Therefore, further work in this area needs to be focused on proposing methods and systems to support teachers during these processes. Prominent examples of such decision support systems are *recommender systems*.

Recommender Systems (RS) are software tools designed to assist users in tackling the information overload problem by highlighting suitable items in a personalized manner (Bobadilla et al., 2013; Manouselis et al., 2013; Drachsler, 2015). They have been used in a wide range of application contexts, such as e-commerce (Huang et al., 2007) and Technology-enhanced Learning (TeL) (Manouselis et al., 2013). In the context of TeL, RS have been primarily utilized for the recommendation of Learning Objects (LO) based on individual teachers' and learners' profiles (Manouselis et al., 2013). Nevertheless, although research on recommendation methods for learners has been extensively considered, teachers have received less attention [**P9**]. Moreover, teachers have also received small research attention in terms of *profiling* methods for capturing and exploiting their personal characteristics (such as their ICT competences) with the aim of providing more personalized recommendations (Dyckhoff et al., 2013).

Taking into consideration the important role of teachers in adopting technology-supported school-based educational innovations (Goktas et al., 2013), the complexity of technology-supported teaching practice (Solar et al., 2013) and the current diversity of individual teachers' digital competences (Sang et al., 2010; Vanderlinde et al., 2014), it is safe to assume that individual teachers' professional ICT competences constitute an important element that can potentially affect the capacity of teachers to engage effectively in their micro/meso level teaching processes, especially designing and delivering their teaching practice using ICT resources and tools. Therefore, a need is identified for decision support systems (e.g., recommender systems) to facilitate teachers during the design (and/or delivery) of their teaching practice using ICT resources and tools, by taking into account their ICT competence profiles.

This need can be defined as a Research Area of the overarching Research Problem, as follows:

- **Research Area #4:** Design, implement and evaluate teacher-oriented recommender systems to support personalization during the process of design of their teaching practice using ICT resources and tools, by considering their ICT competence profiles

In this context, this PhD Thesis aims to investigate the four identified Research Areas and extend the current state of the art in the corresponding research fields through four inter-connected areas of Contribution, as follows:

1. **Contribution #1:** Proposing a framework for profiling the ICT competences of schools as complex organizational entities (**Research Area #1**).
2. **Contribution #2:** Proposing a framework for supporting holistic data-driven school leadership (**Research Area #2**).
3. **Contribution #3:** Proposing a School Analytics framework for supporting school leadership in implementing holistic data-driven decision making (**Research Area #3**).
4. **Contribution #4:** Designing, implementing and evaluating Recommender Systems (RS) to facilitate teachers more effectively engage in their daily tasks of designing and delivering their teaching practice, through the selection of appropriate learning objects based on their unique individual ICT competence profiles (**Research Area #4**).

1.2 Contribution beyond the State of the Art

This section presents the contribution of the thesis for addressing the Research Areas stated in the previous section and extending the corresponding state of the art. The contribution regarding each of the identified Areas is presented in a distinct section.

1.2.1 Contribution #1: School ICT Competence Profiling Framework and ICT Competence Management System Architecture

The contribution of the PhD research relates to the introduction of the concept of **School ICT Competence** from an organizational perspective, and to propose a **School ICT Competence Profiling Framework** for modelling the different dimensions of this concept ([**P5**], [**P8**]). Furthermore, a **school ICT Competence management system** was also designed ([**P2**]).

The proposed framework is built on existing approaches for capturing and depicting the level of ICT uptake of schools, namely the concept of **eMaturity** (Durando et al., 2007; Solar et al., 2013). Moreover, it argued that an extension of these approaches was required, namely for explicitly profiling the ICT competences of the individual staff of the school (i.e., teacher leaders and administrator/principal leaders), which was not evident in the initial eMaturity approaches. The rationale for this extension was that these actors obviously play a vital part in the overall planning and delivery of the school's ICT vision and strategy. Therefore, their specific ICT competences should be explicitly taken into account when measuring the ICT competence level of schools. With the addition of appropriate frameworks for capturing the ICT profiles of their individual staff, schools can monitor not only the processes that these actors are involved in but also the level of their individual competence in carrying them out. The major added value is the capacity of schools to identify reasons for the reported level of competence in certain school function areas and map them to potential issues in the ICT competences of individual staff; therefore allowing targeted improvement actions.

Furthermore, building on the aforementioned conceptual model of school organizational ICT competence, an initial **school ICT Competence management system** was designed ([**P2**]. This system built on the rationale of the school ICT competence framework (i.e., that effective school ICT organizational competence comprises the concept of eMaturity and explicit competence profiling of individual staff) and aimed at providing functionalities for assisting school leaders in capturing, monitoring and updating the level of ICT competence of their school organization.

The designed school ICT competence management system was proposed as a potential means of explicitly facilitating the overview and sustainability of the ICT-related vision of schools. In the context of this PhD, it was proposed given the standpoint taken on the importance of ICT competences of schools in the effective orchestration of all leadership tasks, and more specifically on the ICT competences of the school teachers. The proposed system aims to provide decision support functionalities at school teachers and leaders in terms of capturing, monitoring and updating the ICT competences of individual teachers and the school as an organization.

The results of this research have been published in the following scientific journal, scientific book and international conferences:

- **[P2]** Sergis, S., Zervas, P., & Sampson, D. (2014). A holistic approach for managing School ICT Competence Profiles towards supporting school ICT uptake. *International Journal of Digital Literacy and Digital Competence, 5*(4), 2014.
- **[P5]** Sergis, S., & Sampson, D. (2014). From teachers' to schools' ICT competence profiles, In D. Sampson, D. Ifenthaler, J. M. Spector , & P. Isaias, (Eds.), *Digital Systems for Open Access to Formal and Informal Learning* (pp. 307-327). International Publishing: Springer.
- **[P7]** Sergis, S., Sholla, I., Zervas, P., & Sampson, D. (2014). Supporting school ICT uptake: The ASK school ICT competence management system. In *Proc. of the International Conference on Interactive Mobile and Computer Aided Learning 2014* (pp. 359 – 363), Thessaloniki: IEEE.
- **[P8]** Sergis S., & Sampson, D. (2014). Towards a school ICT competence profiling framework. In *Proc. of the 14th IEEE International Conference on Advanced Learning Technologies (ICALT 2014)* (pp. 759 – 761), Athens: IEEE.

1.2.2 Contribution #2: Holistic Data-driven School Leadership Framework

The main contribution of the Thesis in this area is to propose a holistic framework depicting the core K-12 School Leadership Tasks (SLT) and the institution-wide data requirements for effectively engaging in these tasks. Moreover, work in this research strand aimed to identify leadership tasks which are supported by ICT and could, therefore, benefit from further research in decision support systems incorporating the concept of (school) ICT competence.

Towards formulating the detailed framework of core K-12 school leadership tasks, it was important to study the existing approaches related to leadership tasks in the K-12 school context. The results of this study were:

- the formulation of a core School Leadership Task Framework (SLT), depicting a set of commonly referenced school leader tasks on all institutional layers.
- a critical analysis of existing data-driven decision support systems, in terms of their capacity to fully support the aforementioned SLT

The results of this research have been published in the following scientific book chapter:

- **[P4]** Sergis, S., & Sampson, D.G. (2016). Data Driven Decision Support For School Leadership: Analysis Of Supporting Systems. In J. M. Spector, D. Ifenthaler, D. Sampson, & P. Isaias (Eds.), *ICT in education in global context: Comparative Reports of Innovations in K-12 Education* (pp. 145-171), Berlin Heidelberg: Springer.

1.2.3 Contribution #3: School Analytics: An Analytics framework to support holistic data-driven School Leadership

The main contribution in this area is to build on the results of the Contribution #2 and propose a new Analytics strand, namely *School Analytics*, which transcends the individual confinements of Teaching/Learning and Academic Analytics, in terms of focal points and objectives. More specifically, a critical analysis of existing analytics strands was performed, in terms of their capacity to support holistic decision support required by K-12 school leaders, i.e., for combining «business intelligence» (macro-layer) data and teaching/learning (micro- and meso-layer) data. Building on the insights of this analysis, a new holistic multi-level School Analytics framework was proposed, aiming to integrate and analyze “Business” Intelligence data and Educational/Learning data in an intertwining manner Moreover, the School Analytics framework initially proposed a method of mapping the school leadership tasks of the SLT (proposed in Contribution #2) to institution-wide educational data towards informing holistic school leadership strategic planning.

The results of this research have been published in the following scientific book:

- **[P3]** Sergis, S., & Sampson, D. (2016). School analytics: A framework for supporting systemic school leadership. In J. M. Spector, D. Ifenthaler, D. Sampson, & P. Isaias (Eds.), *Competencies in Teaching, Learning and Educational Leadership in the Digital Age* (pp. 79-122), Springer.

1.2.4 Contribution #4: ICT competence-based Learning Object Recommendations for Teachers

The main contribution in this area is focused on the micro layer of the school organization, towards examining the potential of Recommender Systems (RS) to provide decision support at school teachers towards effective and personalized **learning object (LO) recommendations** for teaching practice design and delivery, with the novelty in our approach being related to the exploitation **of teachers' ICT competence profiles.**

More specifically, the contribution \in the aforementioned field is specifically related to:

- Evaluating the added value of incorporating **teachers' ICT competence profiles** in a **LO recommender system**
- Designing and evaluating a mechanism for **dynamically eliciting teachers' ICT competence profiles**

- Designing and evaluating an extended LO recommender system which dynamically elicits teachers' ICT competence profiles and uses these profiles towards providing ICT-competence-based LO recommendations.

The results of this research have been published in the following scientific journal and scientific conferences:

- **[P1]** Sergis, S., & Sampson, D. (2016). Learning object recommendations for teachers based on elicited ICT competence profiles. *IEEE Transactions on Learning Technologies, 9*(1), 67-80.
- **[P6]** Sergis, S., & Sampson, D. (2015). Enhancing learning object recommendations for teachers using adaptive neighbor selection. In *Proc. of the 15th IEEE International Conference on Advanced Learning Technologies (ICALT 2015)* (pp. 391-393). Hualien: IEEE.
- **[P9]** Sergis, S., Zervas, P., & Sampson, D. (2014). Towards learning object recommendations based on teachers' ICT competence profiles. In *Proc. of the 14th IEEE International Conference on Advanced Learning Technologies (ICALT 2014)* (pp. 534 – 538), Athens: IEEE
- **[P10]** Sergis, S., Zervas, P., & Sampson, D. (2014). ICT Competence-based learning object recommendations for teachers. In *Proc. of the IADIS 11th International Conference on Cognition and Exploratory Learning in Digital Age (CELDA2014)* (pp. 150-157). Porto: IADIS.
- **[P11]** Sergis, S., & Sampson, D. (2014). Eliciting Teachers' ICT competence profiles based on usage patterns within learning object repositories. In *Proc. of the 6th IEEE International Conference on Technology in Education 2014 (IEEE T4E2014)* (pp. 99 - 105), Amrita: IEEE.

1.3 Thesis Overview

This PhD thesis consists of six chapters, as follows:

- Chapter 1 outlines the PhD thesis motivation, problem statement and contributions.
- Chapter 2 is related to **Research Area #1** and discusses the concepts of individual and organizational competence as well as eMaturity and introduces a unifying School ICT Competence Profiling Framework as a holistic means to model the different dimensions of the school ICT competence and a framework for designing school ICT competence management systems. Furthermore, a conceptual architecture of such systems is presented and discussed. This chapter is an adapted and summarizing copy of the following published journal paper and book chapter: (a) "Sergis, S., Zervas, P., & Sampson, D. (2014). A holistic approach for managing School ICT Competence Profiles

towards supporting school ICT uptake. *International Journal of Digital Literacy and Digital Competence, 5*(4), 33-46", (b) "Sergis, S., & Sampson, D. (2014). From teachers' to schools' ICT competence profiles. In D. Sampson, D. Ifenthaler, J. M. Spector , & P. Isaias, (Eds.), *Digital Systems for Open Access to Formal and Informal Learning* (pp. 307-327). International Publishing: Springer"

- Chapter 3 is related to **Research Area #2** and addresses the highly important aspect of data-driven decision making for school leaders and proposes a holistic framework describing the core K-12 School Leadership Tasks (SLT) that school leaders are required to engage with in the emerging context of enhanced school accountability and improvement. Capitalizing on the proposed SLT, the chapter also presents the design and findings of a critical analysis of 70 commercial data-driven decision support systems for school leaders, in order to gain insights on the current state-of-the-art and their capacity to support the SLT. This chapter is an adapted copy of the following published book chapter: "Sergis, S., & Sampson, D.G. (2016). Data Driven Decision Support For School Leadership: Analysis Of Supporting Systems. In J. M. Spector, D. Ifenthaler, D. Sampson, & P. Isaias (Eds.), *ICT in education in global context: Comparative Reports of Innovations in K-12 Education* (pp. 145-171), Berlin Heidelberg: Springer".
- Chapter 4 is related to **Research Area #3** and builds on the results of the previous chapter to propose a new educational Analytics strand, namely School Analytics, which transcends the individual confinements of Teaching/Learning and Academic Analytics and aims to provide more holistic decision support to K-12 school leaders by combining macro-layer data and micro-/meso-layer data. Furthermore, the School Analytics framework proposes a mapping the school leadership tasks of the SLT (presented in the previous chapter) to institution-wide educational data towards informing holistic school leadership strategic planning. This chapter is an adapted copy of the following published book chapter: "Sergis, S., & Sampson, D. (2016). School Analytics: A framework for supporting systemic school leadership. In J. M. Spector, D. Ifenthaler, D. Sampson, & P. Isaias (Eds.), *Competencies in Teaching, Learning and Educational Leadership in the Digital Age* (pp. 79-122), International Publishing: Springer"
- Chapter 5 is related to **Research Area #4** and presents the rationale, design and extensive evaluation of a novel ICT competence-based Recommender System (RS), which aims to provide decision support at school teachers towards effective and personalized learning object (LO) recommendations for teaching practice design and delivery. The chapter discusses the added value and the process of designing a mechanism for dynamically eliciting teachers' ICT competence profiles based on their usage patterns within Learning Object Repositories and the fusion of these profiles in a novel recommender system to generate LO recommendations that are appropriate to meet each teachers' ICT competences. This chapter is an adapted copy of: "Sergis, S., &

Sampson, D. (2016). Learning Object Recommendations For Teachers Based On Elicited ICT Competence Profiles. *IEEE Transactions on Learning Technologies, 9*(1), 67-80"

- Chapter 6 discusses the conclusions of the research work conducted in the Thesis and proposes directions for future research.

2 School ICT Competence Profiling Framework and ICT Competence Management System

2.1 Introduction

Information and Communication Technologies (ICT) have been repeatedly celebrated as a harbinger of teaching and learning enhancement. The diverse range of tools and services currently available has been reported to be beneficial in many aspects of teaching and learning processes (European Commission, 2013a). In order to reap these benefits and provide a driver for change, however, ICT needs to be incorporated into the fabric of schools, and not just be used as a tool for ad-hoc solutions (Micheuz, 2009). Evidence shows that this is not the case, since schools have shown limited exploitation of the full range of ICT potential as an enabler of improved learning and teaching practices (European Commission, 2010; Peña-López, 2015). This occurs despite the substantial advance in terms of technological infrastructure (Durando et al., 2007) and the significant number of initiatives (European Commission, 2011), policy adjustments (European Commission / EACEA / Eurydice, 2012) and new paradigms for professional learning that attempt to battle this inconsistency (Duncan-Howell, 2010).

The reasons for this inconsistency are multi-faceted and multilevel, bearing in mind that schools are, themselves, complex entities with a vast range on interrelating factors (Solar et al., 2013). First of all, teachers, being core actors in the school ecosystem, are usually regarded to have a significant part in the ICT integration process of their institutions (Vanderlinde et al., 2014). More specifically, research has shown that, amongst other reasons, their ICT competences (Sang et al., 2010) and personal attitudes towards ICT use (Tondeur et al., 2010) can greatly affect their level of ICT exploitation, and therefore, influence their schools' ICT strategy. However, teachers are not the only school actor whose actions can affect the institutional integration of ICT. Another significant actor are the school administrators / managers / principals etc. More specifically, their attitudes towards ICT (Tondeur et al., 2010), their ICT strategy planning decisions and the overall culture they cultivate within the school (Law & Chow, 2008) can have an important impact at the level of ICT use. Finally, apart from the human factors, other actors can also hinder ICT uptake in schools, such as ICT access and availability (Pelgrum, 2008) or purely financial matters (Nachmias et al., 2004; Laurillard, 2007).

Taking all the above into account, therefore, the complexity of the issue becomes more evident. The matter of identifying the reasons for the level of school ICT uptake and, more importantly, the paths to remedying for that, is neither straightforward nor trivial. Considering that schools are ecosystems with a wide range of interrelating component elements, the actions of which can affect the whole structure in unique ways (Zhao & Frank, 2003), a holistic standpoint should be taken that effectively encapsulates all of the potential actors and their level of contribution.

Towards addressing this issue, this chapter first presents an overview of the concept of individual and organizational competence, in order to define the essential elements that affect it. Then, a critical discussion is performed on the concept of eMaturity (Durando et al., 2007), which is the current approach towards measuring ICT integration in educational institutions. This critical discussion is performed in order to (a) identify whether this approach, and the frameworks that are used to model and measure it, accommodate the full spectrum of the important elements affecting ICT uptake in schools, as defined by the organizational competence analysis, and (b) to propose a School ICT Competence Profiling Framework, which extends the current eMaturity modelling approaches with the insights from the critical discussion. By doing that, the proposed framework could allow for more holistic representations of the interrelating factors, as well as for the capturing of the level of each factor's contribution to the whole schema. A benefit from such an addition would be to not only detect impediments in the ICT uptake process, but also to assist in the delineation of focused corrective paths.

Finally, the chapter presents the design of a web-based School ICT Competence Management System, which is aligned to the proposed School ICT Competence Profiling Framework. The added value of the proposed system refers to the enhanced functionalities it can offer for (a) capturing and monitoring all levels of schools' ICT Competence Profile (as described in the School ICT Competence Profiling Framework) and (b) combining these (previously) isolated data towards performing diagnoses and generating informed recommendations. These functionalities will potentially assist schools in delineating focused correctional paths and will guide their strategic planning towards organizational improvement (Zangiski et al., 2013).

The rest of the chapter is structured as follows. Section 2.2 provides the essential background on the concepts of individual and organizational competence, which will assist in identifying the core factors that affect school ICT integration processes. Section 2.3 presents an overview of the concept of eMaturity and the existing models for its measurement. Moreover, a critical discussion is performed in order to determine the sufficiency of the existing models to accommodate the full spectrum of school organizational competences. Section 2.4, presents a proposal towards a profiling framework for school ICT competences, which builds on eMaturity but extends to include additional school organizational competence elements. Section 2.5 presents the proposed design of the web-based School ICT Competence Management System. Finally, in Section 6, further work is discussed.

2.2 Background

2.2.1 The concept of Competence

This section presents the concept of Competence, in terms of its two main strands, namely Individual Competence and Organizational Competence.

2.2.1.1 Individual Competence

Individual Competences are a key concept in the areas of human resource management, lifelong learning and performance management (García-Barriocanal et al. 2012; Tripathi & Ranjan, 2013). They can be defined as: "a set of knowledge, skills and attitudes that an individual possess or needs to acquire, in order to perform an activity within a specific context. Performance may range from the basic level of proficiency to the highest levels of excellence" (Sampson & Fytros, 2008).

Given the well-acknowledged importance of the concept of individual competence, a number of different approaches towards individual competence structural representation have been proposed. Some examples include the Iceberg model by Spencer & Spencer (1993), the concentric circle model by Rowe (1995), the five-element model by Cheetham & Chivers with its notion of meta-competences (Sultana, 2009), the boundary approach by Stoof et al. (2002), the holistic approach by Le Deist & Winterton (2005) (also in Winterton, 2009) and the tripartite representation by Sampson & Fytros (2008), with its explicit inclusion of context within the competence definition.

More specifically, apart from the identification of the three main constituents of competence (knowledge, skills and attitudes) and their span in a continuum of proficiency level, the latter definition highlights a key factor that greatly affects the other two, i.e. the context in which the competence is being performed and assessed. The definition of context that this work adopts is "the particular situation in which a practitioner is required to operate" (Cheetham & Chivers, 2005). This notion of context is considered vital, since the level of proficiency of a specific competence is highly dependent on the context in which it is used (Cheetham & Chivers, 2005; Wesselink & Wals, 2011). Moreover, competences themselves differ when performed in different contexts, since the required knowledge, skills or attitudes of the individual are shifted to meet the new requirements of the changing context (Le Deist & Winterton, 2005). Therefore, based on the above, Sampson & Fytros' (2008) holistic conceptualization of individual competence has been adopted in this work.

2.2.1.2 Organizational Competence

Apart from the individual strand, competence has also been identified as a characteristic of organizations. This standpoint has been adopted in this work for the particular context of schools, arguing towards a more holistic view of schools as organizations. This perspective deviates from the approach that views organizational competences as merely the sum of the individual staff competences, since a variety of other actors interplay and produce unique results, even with similar individual inputs (Rakickaite et al., 2011). From this perspective, organizations are considered as "individual" entities that are competent in the specific fields they operate and in the tasks that they perform. Moreover, the high level of competence at organizational level is considered vital to their development (Harris, 2007; Nogueira & Bataglia, 2012) and constant evaluation of the actual outcome must be performed for remedying purposes (Dhillon, 2008).

Before attempting to define organizational competence, we will highlight and clearly outline various concepts which are relevant to the concept of competence and are commonly used in an interchangeable manner. These include the organizational resources, capabilities and competences. Organizational *resources* form the foundational level of organizations upon which their functions are based (Javidan 1998; Zangiski et al., 2013). However, and despite the standpoints of the resource-based view (Gu & Jung, 2013), it is claimed that these assets cannot guarantee organizational success in their own regard. It is the optimal combination and utilization of them that can offer that, i.e. the organizational *capabilities* (Martelo et al., 2013). Furthermore, organizational *competences* describe reified capabilities (routines) that have been well-exercised and have led to measurable outcomes (OpenLearn, 2006). If a specific competence is valued as vital to gaining a strategic advantage over the competitors and to fulfilling the desired goals, then it is described as core competence (Prahalad & Hammel, 1990). Finally, the concept of *dynamic capabilities* describes the ability of an organization to continuously develop its competences by adapting to new circumstances (Sanchez, 2004; Teece, 2007) and, thus, tackling organizational inertia and engaging in organizational learning.

Figure 1 captures a representation of the different concepts from the above analysis that will draw a picture of their position within the organization (Javidan, 1998; Bhamra et al, 2011; Zangiski et al., 2013).

Figure 1: Organizational concept representation

After presenting these clarifications, a review of existing approaches for defining organizational competence was performed, in order to identify the foundational dimensions of the concept. Table 1 presents a summary of existing definitions for organizational competence. All these approaches either define competence explicitly, or use other terms in an interchangeable manner.

Table 1: Organizational competence definitions

	Paper	Organizational Competence definition
1	Prahalad & Hamel (1990)	The collective learning in the organization, especially how to coordinate diverse production skills and integrate multiple streams of technologies
2	Grant (1991)	Capacity… to deploy existing resources to perform some task
3	Barney (1991)	The firm attributes that enable organizations to coordinate and utilize their resources
4	Amit & Schoemaker (1993)	A firm's capacity to deploy resources, usually in combination, using organizational processes, to effect a desired end. They are information-based tangible or intangible processes that are firm-specific and are developed over time through complex interactions among the firm's resources
5	Doz (1997)	Integrative task performance routines that combine resources (skills and knowledge, assets and processes, tangible and intangible) to result in superior competitive positions
6	Drejer (2000)	A system of technology, human beings, organisational (formal) and cultural (informal) elements and the interactions of these elements

7	Hendeghem & Vendermeulen (2000)	A sustainable competitive advantage by unique combination of SKAs [skills, knowledge and abilities) structures, management systems, technologies, and procedures and personnel instruments
8	Maritan (2001)	An organization's capacity to deploy its assets, tangible or intangible, to perform a task or activity to improve the performance
9	Hafeez et al. (2002)	The ability to make use of resources to perform some task or activity
10	Helfat (2003)	An organisational ability to perform a co-ordinated task, utilizing organisational resources, for the purpose of achieving a particular end result
11	Murray & Donegan (2003)	Involve complex patterns of coordination between people, and between people and other resources that lead to sustainable competitive advantage over time
12	Sanchez (2004)	The ability to sustain the coordinated deployment of assets in ways that help a firm achieve its goals
13	Taatila (2004)	An organisation's internal capability to reach stakeholder-specific situation-dependent goals, where the capability consists of the situation-specific combination of all the possible individual-based structure-based and asset-based attributes directly manageable by the organisation and available to the organization in the situation
14	Freiling (2004)	Organizational, repeatable, learning-based and therefore non-random ability to sustain the coordinated deployment of assets and resources enabling the firm to reach and defend the state of competitiveness and to achieve the goals
15	Spanos & Prastacos (2004)	Socially constructed entities, organized in networks of knowledge carrying relations among individuals and inanimate firm assets that, as a whole, aim at performing efficiently and effectively a given task.
16	Gill (2006)	The embodied knowledge set that supports competitive advantage through innovation and flexibility gained by building alignment between the strategic intent, the organizational structure and the expertise of the workforce
17	Lejeune (2006)	Cognitive combinations of existing resources to be activated into new or existing activities so as to reach some targeted outcomes.
18	Ermilova & Afsarmanesh (2007)	The organization's capability to perform (business) processes, tasks, having the necessary resources (human, technological, physical) available, and applying certain standards (practices), with the aim to offer certain products and/or services

19	Edgar & Lockwood (2008)	A set of progressive, iterative understandings and skills held by corporate employees that collectively operate at the organizational level
20	Kraaijenbrink et al. (2010)	[Capabilities] enable the firm to select, deploy, and organize such inputs. [the resources]
21	Rakickaite et al. (2011)	A whole of the potential of internal organizational competence and of external contextualized organizational competence. Internal organizational competence is belonging to employees at individual and collective levels and by an organization is held as important knowledge, skills, abilities, attitudes, values and other personal and collective properties, revealing the potential of organizational competence.
22	Zangiski et al. (2013)	Constructs that mediate this relationship, that is, linking operations strategy to productive resources mobilization, that contribute to operations strategic vision building

An analysis of the above definitions was performed and revealed a set of recurring components. More specifically, three such components are identified, namely the organization's *tangible resources*, the *organizational culture* and the *intangible assets* owned by the organisation, i.e. the individual competences of the staff.

Figure 2 presents the number of appearances of each element in the definitions of Table 1. The definition that best incorporates these elements is the one by Taatila (2004), with the addition of aspects of the external environment, i.e. the stakeholders' perspective.

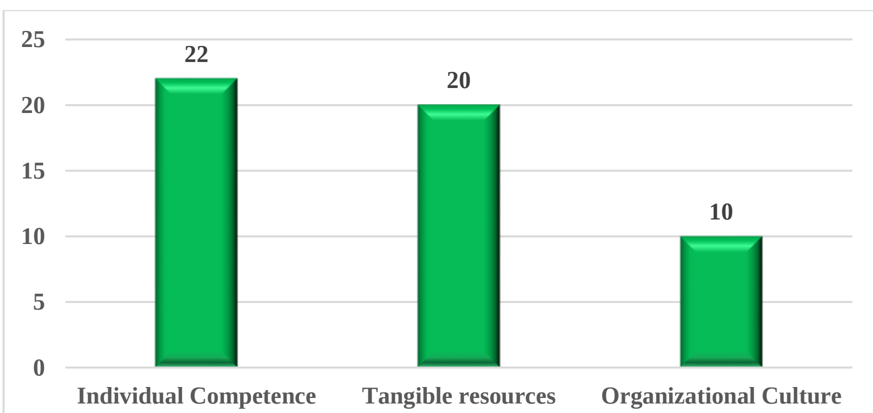

Figure 2: Common elements' occurrence in organizational competence definitions

Therefore, the literature review presented in this section has highlighted the essential elements of organizational competences. This 'framework of analysis' will be utilized in the next section, as a means to review the current approaches to measure ICT integration in schools (namely, eMaturity) and the identification of certain elements that, while being a foundational part of the organizational competence, are currently either insufficiently measured or totally neglected.

2.2.2 The concept of E-Maturity

2.2.2.1 Definition

The concept of eMaturity has been used to describe the level of ICT use in educational institutions (BECTA, 2002). There are two main definitions for eMaturity in the literature. The first, provided by Durando et al. (2007) defines eMaturity as the institution's "strategic and effective use of ICT to improve educational outcomes". The second states that eMaturity is the "organizational readiness to deal with e-learning and the degree to which this is embedded in the curriculum" (Underwood et al., 2010). Both definitions share a common standpoint towards ICT integration, which views technology as being embedded in the educational institutions' processes, rather than just being used in an ad-hoc basis from groups of capable individuals (Micheuz, 2009). The former definition has a formative approach, linking ICT use, and its strategic planning, to educational outcome improvements. The latter appears to take a more summative standpoint dealing with the evaluation of the institution’s existing ICT use and integration.

This dual perspective of eMaturity has spawned a diverse set of frameworks, which mirror these standpoints. An overview of these approaches is presented in the next section. Moreover, an analysis of the different frameworks’ categories is performed in order to identify generic meta-categories that are linked to the eMaturity concept, in general. Finally, the latter are examined to identify the level to which they incorporate the elements of school organizational competence (from section 2.2.1.2) and, thus, the level of their sufficiency to accommodate the representation of all the interrelating factors influencing ICT uptake in schools.

2.2.2.2 Analysis of existing e-Maturity Frameworks

A review of scientific and "grey" literature revealed a set of existing frameworks for the measurement of the level of ICT integration in educational institutions. This process resulted in the identification of 6 frameworks adopting a whole-institutional perspective. These were the NAACE ICT-Mark (NAACE, 2012), the P2P/P2V Inspectorates Framework (European Schoolnet, 2009), the Digital Schools Award (Digital Schools of Distinction, 2013), the ACODE Benchmarks (ACODE, 2014), the E-Learning Maturity Model (eMM) (Marshall, 2007) and the ICTE-M Model (Solar et al., 2013). However, the latter was not fully described in the literature, therefore it could not be meaningfully analyzed. An overview of these frameworks is provided in Table 2.

Table 2: Overview of eMaturity Frameworks

	Name	Metric Categories	Levels	Metrics
1	ICT-MARK	1. Leadership and Management 2. Curriculum Planning 3. Teaching and Learning 4. Assessment of ICT Capability 5. Professional Development 6. Resources	4	57
2	P2V	C1. Leadership C2. Pupil Use C3. Impact on Learning and Standards C4. Infrastructure and access U1. The teaching process U2. Curriculum planning U3. Administrative Use O1. Quality Assurance	4	19
3	Digital Schools	1. Leadership & Vision 2. ICT in the Curriculum 3. School ICT Culture 4. Professional Development 5. Resources & Infrastructure	2	50
4	ACODE	1. Institution policy and governance for technology supported learning and teaching. 2. Planning for, and quality improvement of, the integration of technologies for learning and teaching. 3. Information technology infrastructure to support learning and teaching. 4. Pedagogical application of information and communication technology. 5. Professional/staff development for the effective use of technologies for learning and teaching.	5	73

		6. Staff support for the use of technologies for learning and teaching. 7. Student training for the effective use of technologies for learning. 8. Student support for the use of technologies for learning		
5	eMM	1. Learning 2. Development 3. Support 4. Evaluation 5. Organisation	4	35

As Table 2 depicts, among the existing frameworks, there is a number of recurring metric categories. In order to identify commonalities in these, a further analysis of the contents and focal points of each category was performed, to create a set of unifying, meta-categories. These are described in Table 3, along with their key focal points.

Table 3: eMaturity generic meta-categories

	Category	**Main Focal Points**	**Framework (category)**
1	Leadership for ICT	• Existence of a vision for ICT integration • Constantly evaluated strategy towards its achievement	• ICT MARK (1) • P2V (C1) • Digital Schools (1) • ACODE (1,3) • eMM (5)
2	Curriculum planning / ICT integration in curriculum	• High level of ICT use within and beyond school • Consistent ICT planning throughout the curriculum • Planning for student inclusion • Diverse opportunities for engagement with diverse and emerging ICT • Focus on ICT competence building	• ICT MARK (2) • P2V (C3, U2) • Digital Schools (2), • ACODE (2,4) • eMM (5)
3	ICT in Learning And Teaching Processes	• Manifold and multifaceted use of ICT during the processes • Student Inclusion • Evidence of student ICT competence building	• ICT MARK (3) • Digital Schools (1,2) • P2V (U1, U2, O1) • ACODE (4,7) • eMM (1)

4	ICT Professional Development	• Opportunities for staff professional development are provided • Diverse modes of delivery are promoted • Professional Development has a recorded impact on staff's competences	• ICT MARK (5) • Digital Schools (4) • ACODE(5)
5	Infrastructure and Resources	• Existence and sufficiency of hardware and software • Internal and external connectivity • Existence of e-safety systems • Appropriateness of resources' physical deployment	• ICT MARK (6) • Digital Schools (5) • P2V(C2) • eMM (2)
6	ICT Support Structures	• Existence of Support systems for staff and students	• ICT MARK (6b) • P2V (C2.3) • ACODE(6, 8) • eMM (3)

These meta-categories match at a high degree (and even extend) the generic eMaturity areas mentioned by Harrison et al. (2014), namely connectivity, curriculum ICT policy, school leadership and management planning for ICT and staff development. Similar generic areas have been mentioned by Luger (2007) and Davies & Pittard (2009).

There were two metric categories that were not included in the generic category pool. First, the Digital Schools Award includes a distinct "School Culture" element, but the constituting elements are not unique, meaning that they are represented in alternate categories of other frameworks. Because of this, it was not included in the eMaturity generic categories' pool as a distinct element. Moreover, the eMM and the P2V included specific evaluation metric categories. However, it was not deemed as appropriate for an eMaturity generic category, since evaluation should be embedded within each category, as is the standpoint that the rest eMaturity frameworks take.

The following section presents a critical discussion on the level of sufficiency that the above metric categories offer in terms of adequate accommodation of the elements of school organizational competence, as defined in this chapter.

2.2.2.3 Review of the eMaturity frameworks

The contents of each eMaturity framework, as well as the generic eMaturity categories as described in the previous section, were reviewed, in order to identify the level to which they provided sufficient encapsulation of the elements of organizational competence. This was performed, as aforementioned, with the aims of (a) identifying gaps in the existing ICT integration measurements processes and (b) proposing alternatives for accommodating these shortcomings.

The review process included a binary scale, namely "insufficiently" (if the framework incorporated metrics for an incomplete or non-existent representation of the element) or "fully" (if the element was sufficiently captured by the existing metrics). Concerning the organizational culture aspect, the School Work Culture Profile (SWCP) (Snyder, 1988) was selected for providing a basis for evaluation (see section 2.3). Table 4 presents the results of this review.

Table 4: Review of eMaturity frameworks against organizational competence dimensions

Framework	Individual ICT Competences		Tangible Assets	Organizational Culture
	Teacher	Administrator		
ICT-MARK	×	✓	✓	✓
P2P-P2V	×	×	✓	×
eMM	×	×	✓	×
Digital Schools	×	✓	✓	×
ACODE	×	✓	✓	×
Generic Categories	×	×	✓	×
* ✓ signifies Full integration, × signifies Insufficient integration				

As Table 4 depicts, only the tangible assets are universally and adequately represented by the existing frameworks. Moreover, a significant issue is the universal lack of a method for capturing teachers' ICT competences. The administrator competences are indirectly, addressed in some cases under the "Leadership" eMaturity category, but these implementations do not provide a solid method for assessing which ICT competences an administrator or leader should possess in order to drive their school (with its unique competences) towards full ICT exploitation. The same rule applies to the "Organizational Culture" element.

The above issue of inadequate accommodation of the individual staff ICT competences (i.e. teachers and administrators) is deemed as crucial since these actors obviously play a vital part in the overall planning and delivery of the school's ICT vision and strategy. Therefore, their specific ICT competences should be explicitly taken into account when measuring the ICT competence level of schools. With the addition of appropriate frameworks for capturing these elements, schools can monitor not only the processes that these actors are involved in but also the level of their individual competence in carrying them out. The major added value could be the ability of schools to identify potential reasons for the reported level of competence in certain school function areas. For example, the eMaturity approach would state a fact that the school shows low level of ICT uptake in specific "teaching processes". However, without an explicit ICT competence profile of all the teachers who are planning and delivering the lessons, it would be difficult to identify that a group of teachers (who can be identified) lacks a specific set of necessary competences, a fact that ends up impeding the overall processes and school-wide strategies. Moreover, analyses can be performed to match/benchmark the individual ICT competences of school actors and the overall school performance, in order to further enhance the level of overview that the school has on its function and its progress over time.

Apart from the explicit lack of representation for specific organizational competence elements, the content analysis of the existing frameworks highlighted two additional areas that could potentially hinder the effective measurement of school ICT uptake and the meaningful interpretation of the results. More specifically, despite the fact that the frameworks' categories can be semantically grouped in unified meta-categories, the fact that each framework uses diverse metrics for evaluating the same school area's ICT performance, can prove to be a hindrance in the universal recognition of the results. This fact is further enhanced by the lack of a universal measurement scale in these approaches. Moreover, another issue is related to the fact that the interrelating factors affecting each metric are almost never identified. This shortcoming is related to the previously mentioned added value of utilizing staff ICT competence profiles. The identified issue is that schools can be aware of a general area where they underperform, but have no specific information on the exact sub-elements that hinders their performance, and, therefore, receive limited guidance or suggestions on how to amend for it.

Finally, another issue (not related to framework content) that could hinder the existing frameworks' ability to enable school ICT improvement is related to the context within which they are used. More specifically, two frameworks (namely the ICT-MARK and the Digital Schools Award) take an explicit accreditation-oriented approach towards eMaturity. This means that they target on external, official inspection for providing accreditations. This fact, despite lending motivational boost for the participation of schools, may lead to window-framing situations where the actual reality in the school is hidden or there are targeted improvements only to the elements under inspection (Ossege, 2012). In addition, school staff members have expressed their disapproval for this type of accountability to external bodies in favor of actual school improvement initiatives (Knapp & Feldman, 2012).

In the light of all the above issues, it is evident that the current implementations of eMaturity do not offer metrics for capturing and evaluating key elements affecting the level of school ICT integration. Therefore, it is important to extend the current approaches in order to accommodate such improvements. To address this issue, and to allow for a more granulated, overall, evaluation method, an alternative approach has been developed and is presented in the following section. More specifically, the proposed framework builds on the eMaturity frameworks, extending them for including the individual competences of the schools' staff and, also, providing more granulated metrics for all the areas, based on commonly used competence frameworks.

2.3 Proposed School ICT Competence Profiling Framework

As aforementioned, the proposed School ICT Competence Profiling framework is based on the eMaturity frameworks but aims to extend them in order to incorporate essential elements of the school organizational competence as it was defined in this chapter, i.e. as a three-dimensional entity. This approach aims for the representation of schools' ICT competences (and, potentially, educational organizations in general) in a detailed and unified manner, based on commonly used competence frameworks. Figure 3 depicts the proposed School ICT Competence Profiling framework in terms of the constituent dimensions.

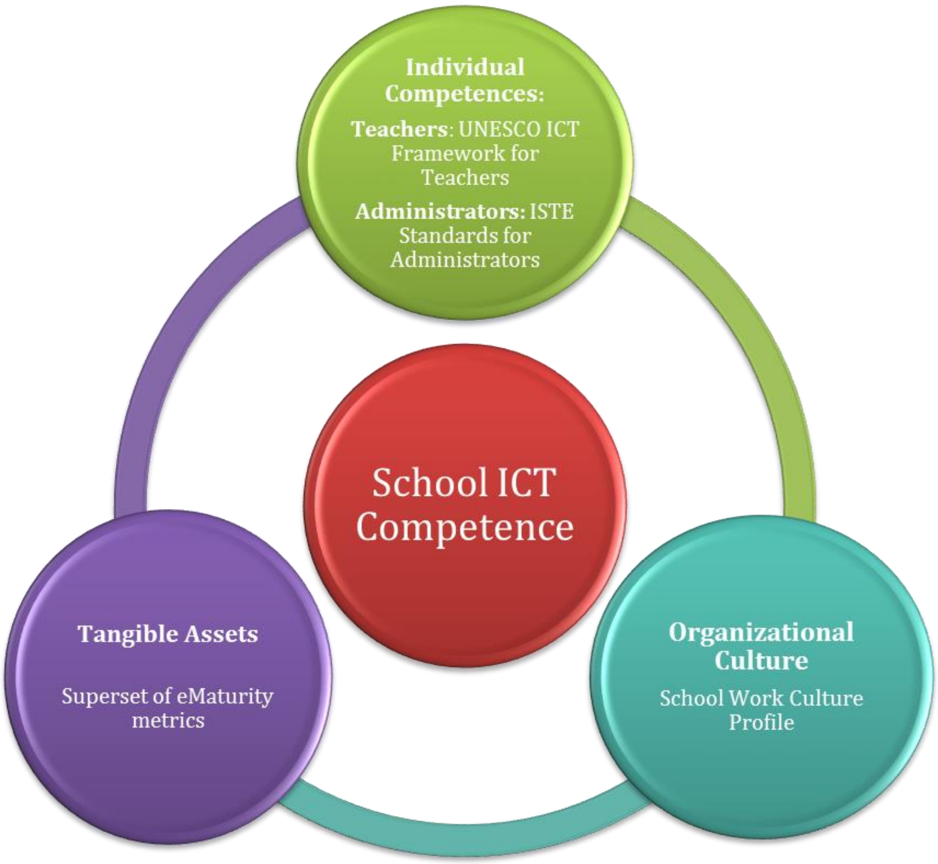

Figure 3: Overview of the School ICT Competence Profiling Framework

The following subsections present, in detail, each of the proposed framework's dimensions.

The individual competences dimension

The individual competences of the school address the competences of the core human actors affecting the design and implementation of the schools' strategic plan, namely the teaching staff and the principal/administrators. This dimension refers to the ICT competences that the individuals should possess in order to perform in a competent manner. This is a major addition which aims to tackle the significant lack of accommodation of such data from the existing approaches.

The competences related to this dimension are derived from existing well-known and widely used individual competence frameworks. More specifically, the UNESCO ICT Competency Profile for Teachers (UNESCO, 2011) is used for the teachers' ICT competences and the ISTE Standards for Administrators (ISTE, 2009) for the administrators' ICT competences.

The UNESCO ICT Competency Profile for Teachers has been developed with the aim to assist teachers in using ICT for improving students' learning. It incorporates 6 competence categories, namely Understanding ICT in Education, Curriculum and Assessment, Pedagogy, ICT, Organization and Administration, Teacher Professional Learning. Furthermore, it defines 3 proficiency levels (or approaches), which are Technology Literacy, Knowledge Deepening and Knowledge Creation. The rationale for selecting this framework is its credibility, which is verified by the standing of the developing body and its wide scope and recognition (Zervas et al., 2014).

The ISTE Standards for Administrators has been developed by the International Society for Technology in Education with the aim to provide a set of competences needed by school administrators in order to be able to support digital age learning and transform the educational landscape. The Standards include 5 areas, namely Visionary Leadership, Digital Age Learning Culture, Excellence in Professional Practice, Systemic Improvement and Digital Citizenship. Each area is divided in a number of competences. The ISTE Standards for Administrators were used since it is the only identified framework addressing the subject of ICT competences of school administrators.

The proposed approach for representing individual ICT competences offers a commonly recognized, granulated and robust manner to capture significant elements of the school ecosystem that were currently either indirectly addressed or totally ignored. Also, it does not add a significant cost to the overall process, since these metrics can be self-administered.

The tangible assets dimension

The tangible assets field mainly refers to the infrastructure of the school. To the best of our knowledge, there is no existing model for capturing organizational infrastructure elements and, therefore, bearing in mind the adequate representation of this element from the majority of existing eMaturity approaches, a superset of these metrics was created. A content analysis was performed to identify overlapping elements and the resulting list was enhanced with items focused on the strictly quantitative capturing of certain aspects, e.g., the exact number of functional computers in the school.

The list comprises a set of 8 areas related to the tangible assets of educational institutions, which can be populated and measured using Likert scales (where appropriate). The metric categories used in each category aim to capture both actual data on the current infrastructural state and perceived data on the levels of use and efficiency of the different asset categories. The proposed composed list is presented in Table 5.

Table 5: Proposed metric categories for modelling organizational Tangible Assets dimension

	Area	Framework	Metric Categories					
1	**Hardware**	• ACODE, • P2V • Digital Schools • ICTE-MM • eMM	Place within school	Type of hardware (e.g., printer, PC)	Number of functional devices	Specifications of each hardware item	Level of Access for teaching	
2	**Software**	• ICT-MARK • P2V • eMM • Digital Schools	Title	Number of licences	Subject Domain relevant to software item	Up-to-Dateness	Sufficiency in terms of curriculum	Access to all students
3	**Procurement Strategy**	• ACODE • P2V • ICT-MARK • eMM	Existence (Y/N)	Efficiency	Specific and adequate budget	Evaluation of school asset needs	-	-
4	**Connectivity**	• Digital Schools • ICT-MARK	Type of connectivity	Connection Speed	Access to all students	Reliability		-
5	**Management System**	• ICT-MARK	Existence (Y/N)	Access to all stakeholders	Level of student administrative use	Level of managerial use	Efficiency	-
6	**E-Learning Spaces**	• P2V • ICT-MARK • Digital Schools	Existence (Y/N)	Access to all	Level of teacher use	Level of student use	-	-
7	**Systems for digital security**	• P2V • ICT-MARK • Digital Schools	Existence (Y/N)	Type	Efficiency	-	-	-

8	**Technical support**	• ACODE • P2V • ICT-MARK • eMM	Existence (Y/N)	Number of support staff	Sufficiency for school needs	Availability	Efficiency	-

The added value of the proposed approach is that it offers a unifying and overarching metric category set that encapsulates all the major focal points of the eMaturity frameworks. It can, therefore, allow for interoperable results that can be used for universal recognition of the schools' achievements.

The organizational culture dimension

Regarding the school culture element, it was deemed important for inclusion in the proposed framework, since it was identified as a vital element of organizational competences, but was almost universally neglected from the eMaturity approaches. Additionally, the literature argues towards the school culture's importance for effective ICT integration in schools (Somekh, 2008).

Numerous existing models for measuring organizational culture are available. A detailed review of this research area has been published by Jung et al. (2007). A fraction of these focuses on the specific context of schools (Maslowski, 2006). This small pool of candidates was considered for the purpose of identifying an appropriate model for the proposed framework for school ICT competences. The candidate models were:

- The Organizational Culture in Primary Schools (OCPS) (Houtveen et al., 1996).
- The Schools Values Inventory Form III (SVI) (Pang, 1998).
- The School Cultural Elements Questionnaire (SCEQ) (Cavanagh & Dellar, 1996).
- The School Work Culture Profile (SWCP) (Snyder, 1988).
- The Professional Culture Questionnaire for Primary Schools (PCQPS) (Staessens, 1990).
- The School Culture Survey (SCS) (Saphier & King, 1985)
- The School Quality Management Culture Survey (SQMCS) (Detert et al., 2003).

The process of selecting the most appropriate model for representing School Culture was facilitated by the work of Schoen & Teddie (2008), who identified four key elements that school culture conceptualizations should include. They were described as follows:

- "Professional Orientation", which incorporates the attitudes and activities that signify the level of professionalism in the faculty in terms of development and school improvement.

- "Organizational Structure", which includes aspects related to leadership type, levels of communication between staff, internal/external accountability and the development of common vision/mission for the school.
- "Quality of Learning Environment", which refers to the extent of opportunities provided by the school for students to engage in meaningful challenges. It must be noted that this dimension can be integrated in the premises of the UNESCO ICT Competency Framework for Teachers and, therefore, was not included in the selection process.
- "Student-centered focus", which incorporates the level of individual student needs' support and assessment.

These dimensions are a superset of similar ones proposed by Zhu et al. (2011).

The aforementioned dimensions of school culture were used as a basis for evaluating the candidate models against. In addition to these criteria, the latter had to clearly adopt an entire school perspective. Under this light, a set of models did not qualify and were eliminated from the list. These were the SCS and the SCEQ, which were mainly focused on teachers. Moreover, the SQMCS model was not included due to the low validity (Cronbach's alpha) associated to its elements (Detert et al., 2003).

The results of the comparison of the remaining four candidate models are presented in Table 6.

Table 6: Comparison of School Culture Frameworks

	Model	**Validity (Cronbach's alpha)**	**Dimensions of Organizational Culture**		
			Professional Orientation	Organizational Structure	Student-Centered Focus
1	SWCP	0.88 - 0.97	✓	✓	✓
2	PCQPS	0.89 - 0.95	×	✓	×
3	SVI	0.73 - 0.92	✓	✓	×
4	OCPS	0.70 - 0.89	✓	✓	×

*✓ signifies full incorporation and × signifies no incorporation

As Table 6 depicts, "Professional Orientation" and "Organizational Structure" are elements that are almost universally present in the candidate models. On the other hand, the "Student-centered focus" element is only adequately represented by the SWCP model. Moreover, the SWCP model has been reported to have a high validity coefficient.

As a result of the above, the SWCP model was identified as the most appropriate for inclusion in the proposed School ICT Competence Profiling framework. The model consists of four domains, namely "Schoolwide Planning", "Professional Development", "Program Development" and "School Assessment", each comprising 15 metrics (for a detailed analysis, see Quin, 2012). The model's areas and metrics cover a wide range of school functions, including intra-staff relationships and collaboration, hierarchical communication, school-wide planning and, even, provide for the inclusion of parents in these processes. For these reasons, and the fact that it boasts a very high level of validity, this model was deemed as the most appropriate for incorporation in the proposed School ICT Competence Profiling Framework.

2.4 Proposed School ICT Competence Management System Architecture

As aforementioned, the proposed School ICT Competence Profiling Framework aims to provide a more granulated method to capture the schools' level and quality of ICT uptake by taking into account additional educational data regarding the schools' individual staff competences and combining them to the data collected by existing eMaturity approaches. By exploiting this extra level of information, the school leader can delineate focused correctional actions, e.g. organize targeted professional development activities for the teachers with the low-level ICT Competences or more optimally exploit and manage the tangible resources of the school. Nevertheless, performing these tasks, and more significantly, planning the paths to remedy, is a time-consuming and difficult endeavor. The complexity involved becomes more overwhelming considering the lack of existing tools for facilitating these processes and generating informed recommendations on school-wide level, based on the combination of available data.

In the light of the above, the design of a (web-based) system that aims to tackle these shortcomings was performed. More specifically, the section presents the design architecture and the core functionalities of a School ICT Competence Management System. The design of this system comprises three conceptual Modules, namely the Diagnostic Module, the Recommendation Module and the Remedy Module, as follows.

- **The Diagnostic Module**. This module includes mechanisms for capturing and visualizing the teachers' ICT Competence Profiles and the schools' eMaturity level. The retrieved data are utilized for diagnostic purposes, i.e. for processing and visually depicting the current level of the School ICT Competence profile. This has the potential to assist school teachers and school leaders have a detailed overview of their own and their schools' level of ICT Competence and initially plan for improvement in the areas identified as underperforming.

- **The Recommendation Module.** This module includes the mechanisms that translate the generated diagnostic data to targeted recommendations for strategic school planning.
- **The Remedy Module.** This module includes the mechanism for updating the schools' ICT Competence profile. More specifically, based on the outcomes from the generated suggestions of the Recommendation Module, different elements of the School's ICT Competence Profile can be appropriately updated, either automatically or manually.

The detailed analysis of the proposed School ICT Competence Management System architecture, user groups and functionalities is presented in the following sections.

2.4.1 User Groups

The School ICT Competence Management System aims to target two main user groups, namely school teachers and school leaders. Each user group is described as follows:

- **School Teachers:** this user group relates to (a) the individual school teachers of the registered to the system schools and (b) school teachers that would like to be recruited by the registered schools. Functionalities aimed at this group should include mechanisms for submitting and updating their ICT Competence Profiles. Moreover, teachers should be provided with a comprehensive tool for monitoring their current level of ICT Competence as well as its progress over time within a given timeframe. Moreover, they should be provided with recommendations for professional development courses towards improving their current ICT competences. These improvements should be automatically updating their ICT Competence Profile, as well as the eMaturity Profile of the school in which they are employed.
- **School Leaders:** this user group relates to the schools' leaders of the registered to the system schools and its functionalities should be targeted both at school-wide level, as well as at individual school teacher level. The reason for this dual focus is related to the need of school leaders to have a highly granulated overview of both the main processes performed in their institutions as well as the specific profiles of their faculty. More specifically, at school-wide level, the proposed system should include mechanisms for submitting, updating and visualizing school's eMaturity Profile as well as highlight areas of potential improvement. In addition, tools for detailed monitoring and management of the level of school ICT Competence profile should be available both on the basis of a current proficiency level at a specific point in time, as well as its progress over time within a given timeframe. At individual teacher level, the system should facilitate the faculty management process by allowing the school leaders to view the level of ICT

Competence of each teacher employed in their school. Moreover, the school leaders should be provided with recommendations for recruiting suitable and available teachers based on their Schools ICT Competence Profile. These recruitments, when confirmed by school leaders, should automatically be updating their Schools' ICT Competence Profile.

2.4.2 System Architecture and Modules

The School ICT Competence Management System is a web-based system that allows school teachers and leaders to measure and continuously monitor the level of their schools' ICT Competence, by providing both their teachers' ICT Competence and School eMaturity profiles correspondingly. The system should then employ specialized mechanisms for jointly processing these data and generating strategic planning recommendations and remedy actions towards enhancing the level and quality of school ICT uptake. Figure 4 presents an overview of the School ICT Competence Management System.

As shown in Figure 4, the lowest level includes XML Native Databases, which host the ICT Competence Profile of the schools registered to the system (namely the employed Teachers' ICT Competence Profile and the School eMaturity Profile), as well as the ICT Competence profiles of candidate teachers for recruitment. The next level includes the profile matching mechanism, which is responsible for performing similarity matches between (a) the ICT Competence Profiles of teachers, who are not employees of the registered schools and (b) the eMaturity Profiles of these schools, towards providing input to the recommender module of the top level for targeted job positioning. The details of this process are described in the corresponding Recommender Module below. Finally, the top level of the system comprises three main modules, as follows:

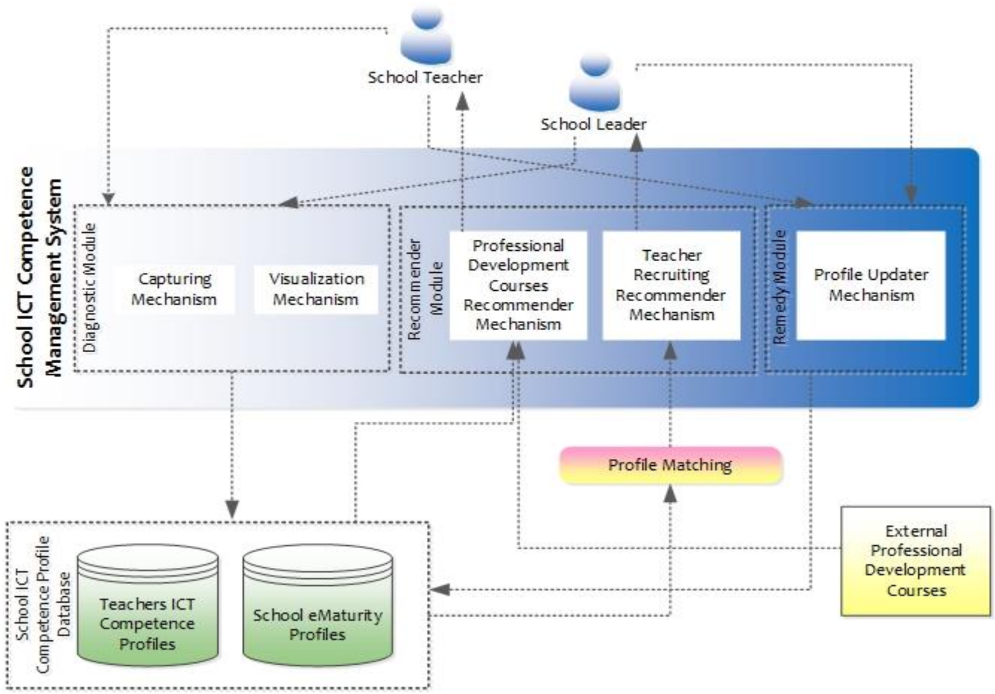

Figure 4: School ICT Competence Management System Architecture

- **The Diagnostic Module:** This module is related to the most basic functionalities of the system, which are mainly focused on capturing and visualizing the current level of schools' ICT Competence profiles. More specifically, it includes the following mechanisms:
  - *Capturing Mechanism:* this mechanism is used by school teachers and leaders for manually submitting and updating their ICT Competence Profiles, as well for submitting and updating the level of school eMaturity correspondingly. Moreover, the submitted teachers' or schools' profiles are captured in a machine-readable manner, namely in XML format. This is done to allow for advanced processing functionalities and interoperability among different systems, e.g., the externally hosted repositories of the professional development courses.

    To this end, a review has been performed on the existing means of performing this task, i.e. the existing specifications for describing competences, which was presented in detail in (Zervas et al., 2014). The "Integrating Learning Outcomes and Competences" (InLOC) specification (Hoel & Grant, 2013) was deemed as the most robust, based on a critical analysis of the major competence description specifications. Therefore, the InLOC specification was selected for the description of both teachers' ICT Competences, as well as the schools' eMaturity profiles.
  - *Visualization Mechanism:* This mechanism can be utilized from school teachers for diagnostic purposes, namely for processing and visually depicting the current level

their current level of ICT Competence as well as its progress over time within a given timeframe. Moreover, this mechanism can be also used by school leaders for performing similar operations for their Schools eMaturity profile, as well as for each teacher employed in their schools. This mechanism should also highlight areas in need of potential improvement in terms of schools eMaturity profile in order to support leaders to address relevant issues.

- **The Recommender Module:** This module retrieves and analyzes the data that have been stored from the Diagnostic module towards generating informed and personalized recommendations. More specifically, it includes the following mechanisms:
    - *Professional Development Courses Recommender Mechanism:* this mechanism aims to recommend to school teachers targeted professional development courses that are stored in external sources. The recommended courses should be appropriate for supporting individual teachers to enhance areas of their ICT Competence in which they show a low level of proficiency. The recommender mechanism should consider as input the teachers' current ICT competence profile and the context that this is applied, namely the school eMaturity Profile and should recommend appropriate professional development courses for targeted ICT Competence enhancement. In case that these courses' learning outcomes are modeled based on the specific UNESCO ICT-CFT competences they target to build, the participating teachers' ICT competence profile could be automatically updated (upon completion of the course) by the Remedy module. Otherwise, the Remedy module will expect for manual input (by the school teacher or the school leader) of the ICT competences attained towards updating their profile.
    - *Teacher Recruiting Recommender Mechanism:* this mechanism aims to recommend to school leaders suitable and available teachers by considering the School ICT competence Profile. The candidate teachers' ICT Competence profiles are stored in the same database as the "employed" teachers, with the difference that they are not linked to a particular school. These teachers will have appropriate ICT Competence Profiles that provide an added value to the overall School ICT Competence profile, based on its current needs. This mechanism should also receive input from the profile matching mechanism that has been previously described.
- **Remedy Module:** This module receives input from both school teachers and school leaders as a result of their actions performed based on the recommendations suggested from the recommender module. More specifically, the Remedy module main contribution is the *profile updater mechanism*, which aims to support semi-automatic update of the School ICT competence Profile. This means that when a teacher completes

a suggested professional development course, the system should be able to update (automatically or manually) his/her ICT competence profile accordingly to the attained or updated ICT Competences. Moreover, the eMaturity Profile of the current school that this teacher belongs to, should also be automatically updated, since the enhanced competences of the teachers directly affect specific elements of the school eMaturity level. Similar updates in the School ICT Competence Profile should be performed upon altering of the other dimensions of the profile, e.g., procurement of new equipment or

2.5 Conclusions

This chapter presented a proposal for a unified School ICT Competence Profiling Framework. This proposal was based on a literature review on the concept of competence, both at the individual and organizational level, and a critical evaluation of the existing approaches towards the measurement of ICT integration levels in educational institutions. This process highlighted a set of shortcomings, the most significant of which were the lack of robust and explicit methods for capturing the ICT competences of key elements of the school ecosystem. This is an important drawback, since it can significantly hinder the organization's ability to identify factors that impede the progress of its strategic ICT planning, as well as its capacity for effective future planning. Therefore, the proposed framework takes a step towards addressing these drawbacks and providing a more detailed basis for schools to engage in effective capturing, monitoring and evaluation of their ICT competences.

Therefore, the proposed School ICT Competence Profiling Framework has the potential to offer not only a detailed and highly granulated means of capturing the current level of ICT usage at school level, but also, and perhaps more importantly, a clearer view of the exact elements of school function that hinder the overall development of the institution and, thus, assist in constructing targeted corrective paths.

Furthermore, considering the evident difficulty of schools in engaging in these complex endeavors, a significant need emerges for dedicated support systems that will offer functionalities for facilitating schools in capturing and interpreting their ICT Competence Profile data. Moreover, the lack of relevant existing systems further strengthens the need to tackle this identified problem. Towards addressing the aforementioned need, the chapter presented the architecture and the core functionalities of a proposed web-based School ICT Competence Management System. More specifically, the proposed system aims to tackle the existing previously identified problems by providing a tool for schools to effectively capture and meaningfully interpret both levels of their ICT Competence profiles in a holistic manner, i.e., by considering the interrelations of these levels. Moreover, it outlines the incorporation of recommender systems for generating targeted suggestions for improvement based on the harvested data and the resulting analyses. An initial implementation of some modules of the proposed system have been presented in (Sergis et al., 2014b **[P7]**).

The following chapter extends the discussion on supporting school leadership to orchestrate the functions of school in a data-driven manner, by modelling the specific tasks that school leaders need to perform and investigating the current state-of-the-art in the existing decision support systems that aim to scaffold these tasks.

3 Holistic Data-driven School Leadership Framework

3.1 Introduction

As previously analysed, schools are in essence 'complex adaptive systems', comprising a wide range of interrelating actors including (among others) the leaders, the teachers, the students and their parents, infrastructure, as well as policies (Lai & Schildkamp, 2013; Trombly, 2014). More specifically, within schools these actors generate a wide range of educational data across three school layers, as follows:

- **Micro layer**, which refers to the learning and assessment practices occurring either within the physical educational organization premises or beyond them (Mandinach, 2012; Kaufman et al., 2014; Van der Kleij et al., 2015).
- **Meso layer**, which refers to the monitoring and evaluation of the teaching practices and curriculum planning of the school (Ifenthaler & Widanapathirana, 2014).
- **Macro Layer**, which refers to the organizational development (Business Intelligence) processes of the educational organization (Marsh et al., 2006; Kaufman et al., 2014).

In this context, (school) Complexity Leadership is primarily addressed at orchestrating such complex adaptive systems (Schneider & Somers, 2006). This approach allows for a more distributed standpoint for leadership, where strategic planning is not solely devised by a single actor (administrative leadership), but is also the result of the interactions of other system actors such as the students, teachers and infrastructure (adaptive leadership) (Lichtenstein et al., 2006; Uhl-Bien et al., 2007). Therefore, towards capturing these interactions and generating informative feedback loops for influencing school system emergence, it is critical to enable and sustain a constant flow of institution-wide educational data (Uhl-Bien et al., 2007).

Following this approach, school leaders, namely principal leaders and teacher leaders (OECD, 2013c), are recognized as a highly influential actor for school organizational performance (Sun et al., 2013; Wallace Foundation, 2013; Hauge et al., 2014), both in terms of high quality educational outcomes (Robinson, 2007; European Commission, 2012), as well as for sustaining school organizational improvement and staff development (European Commission, 2013b; Liou et al., 2014). Moreover, these processes are becoming increasingly challenging considering the global push towards school autonomy and accountability, which assign more degrees of freedom (and, thus, responsibility) to school leaders (Knapp & Feldman, 2012; West et al., 2014).

Therefore, it is evident that school leaders face complex multi-criteria decision making problems, which require holistic and highly granulated support mechanisms (Olson, 2008). In response to this, data driven decision making in education has received an increasing level of attention and emphasis, on a global scale (Knapp et al., 2006; Park & Datnow, 2009; Lai &

Schildkamp, 2013). As a process, similar to the standpoints of Complexity Leadership, it refers to the collection, analysis, and interpretation of institution-wide educational data towards generating ‘feedback loops’ (in the form of insights) for informing leadership in educational settings (Mandinach, 2012). Educational data are defined as “information that is collected and organised to represent some aspect of schools. This can include any relevant information about students, parents, schools, and teachers derived from qualitative and quantitative methods of analysis.” (Lai & Schildkamp, 2013). Employing data driven decision making processes is considered to be instrumental towards effective school organizational leadership and development (Lai & Schildkamp, 2013; Gill et al., 2014; Schechter & Atarchi, 2014).

However, the actual exploitation of these institution-wide feedback loops from school leaders is usually hindered due to several reasons including time constraints and the required competences of the school leaders to analyze the collected data and identify solutions (Marsh & Farrell, 2014). Moreover, the level of availability and quality of institution-wide data collection and processing greatly influences the capacity of the leaders to engage in their school leadership tasks (Marsh et al., 2006; Ikemoto & Marsh, 2007). Considering these impeding factors, and taking also into account the facts that (a) schools are complex adaptive systems with a wide range of interrelating actors in both institutional layers contributing to their overall state of performance (Snyder, 2013), and (b) school autonomy and accountability are being globally pursued and promoted (Hooge et al., 2012; OECD, 2014a), a need is identified for school leadership decision support systems (SL-DSS) that will address the core school leaders' tasks and will effectively facilitate their decision making processes based on the provided institution-wide feedback loops (Kaufman et al., 2014).

Under the light of the above, this chapter (a) proposes a holistic School Leadership Task framework (SLT) for outlining the key tasks that school leaders engage with in terms of school-wide decision making and (b) performs a critical quantitative analysis of existing SL-DSS, in terms of their capacity to adequately support the SLT. The insights from this critical analysis are utilized to drive future implementations of SL-DSS towards providing more effective data driven decision making affordances for school leaders.

The remainder of the chapter is as follows. Section 3.2 defines the background of this work. More specifically, it reviews the landscape related to school (complexity) leadership as well as the related core school leadership tasks and their institution-wide data requirements. The aim of this section is to formulate the holistic School Leadership Task framework. Section 3.3 presents the methodology and results of the critical analysis of 70 existing school leadership decision support systems, benchmarked against the developed SLT. Finally, Section 3.4 presents the conclusions drawn from the previous analysis, towards identifying recommendations for future SL-DSS that will facilitate school leaders in performing the full spectrum of their tasks and engaging in effective school-wide decision making.

3.2 Background

3.2.1 School Leadership

3.2.1.1 Definition

In the existing literature, there are different and sometimes, contradicting, definitions of School Leadership derived from the different perspectives of Leadership as well as, the different Educational Policies (Yukl, 2002; Leithwood et al., 2006; Bush & Glover, 2014). A commonly cited definition of school leadership is "a process of influence leading to the achievement of desired purposes, requiring successful leaders to develop a vision for their schools based on their personal and professional values" (Bush & Glover, 2003). Therefore, school leadership can be regarded as a “social” influence process which involves (a) the formulation of a vision for (holistic) organizational progress from leader(s) and (b) the continuous sharing and "influencing" of other individuals or groups towards achieving this vision (Bush, 2008; Park & Datnow, 2009; OECD, 2013c).

A clarification should be made at this point, regarding the terms "school leadership" and "school management" (and “administration”) given that it is common for the two terms to be used interchangeably as identical (OECD, 2013c). The term *school management* (and administration) mainly refers to tasks related to the maintenance of present operations and resources of the organization. The term *school leadership* has emerged, first as an alternative, mainly referring to tasks related to vision building, strategic planning and the creative formulation of action plans for school organizational improvement (Bush & Glover, 2014). However, it is becoming increasingly evident that effective and holistic school organizational development requires both these two capacities as equally important and, in fact, complementary (OECD, 2008; OECD, 2013c; Bush & Glover, 2014). Therefore, adhering to this notion, this book chapter will adopt an overarching conceptualization of *school leadership*, which will however fully engulf the concept (and related tasks) of school management. More specifically, school leadership tasks considered in this chapter will include both management tasks (as they were previously presented), as well as strategic organizational planning for changes.

Furthermore, the concept of school leadership has undergone another transformational procedure in terms of (a) "who" the school leader is (power balance) and (b) "what" specific area of the school organization the school leader is explicitly leading (Bush & Glover, 2014). More specifically, initial forms of school leadership advocated in favor of a sole power position (e.g., the individual principal) which was responsible for leading the school as an educational organization addressing specific function areas, e.g., overseeing the teaching practices within the classroom (instructional leadership) or orchestrating the managerial tasks of the school (managerial leadership) (Hendriks & Scheerens, 2013; Bush & Glover, 2014).

However, such restrictive conceptualizations of school leadership have been superseded by novel approaches, mainly because they have been attributed with poor organizational performance (Leithwood et al., 2006; Oswald & Engelbrecht, 2013). More specifically, a paradigm shift has gradually occurred promoting more distributed leadership paradigms. These approaches advocate for (a) tipping the power balance towards more apportioned leadership which engages other school actors such as teachers (Bush & Glover, 2012; Gurr & Drysdale, 2013) and thus, (b) expanding the range of organizational function areas being subject to scrutinizing leadership towards a more holistic approach (Leithwood et al., 2006; Bush & Glover, 2012; Dimmock, 2012).

This shift has also been promoted to accommodate the emerging conceptualizations of schools as **Complex Adaptive Systems** (CAS). Complex Adaptive Systems (CAS) within the context of complexity theory are systems comprising a wide range of actors which co-exist, interplay and constantly evolve at different layers of the System, influenced by the actions of other actors towards achieving optimal fitness within the System as a whole (Hmelo-Silver & Azevedo, 2006; Wallis, 2008; Huang & Kapur, 2012). This vast web of interconnections and interactions between the involved actors produce data that can affect the actions of the actors by generating constant feedback loops to these actors (Holland, 1998; Trombly, 2014). Furthermore, these feedback loops and the collective behaviors of the actors result in the formulation of the System status in a process known as emergence (Holland, 1998; Lichtenstein et al., 2006; Miller & Page, 2007). The basic notion behind emergence is that each current status of the system is not a linear sum of its constituent parts but has been forged in a networked and unpredictable manner by the characteristics and interactions of its actors (Uhl-Bien & Marion, 2009).

Furthermore, a key aspect of Complexity Leadership is related to enabling and sustaining a constant flow of data and inter- actor interactions, which are required for generating feedback loops and, ultimately, system emergence (Uhl-Bien et al., 2007; Uhl-Bien & Marion, 2009). Thus, it is commonly acknowledged that leadership efforts should be placed on mechanisms for capturing, collecting, modeling and analyzing these interactions and their related, institution-wide data (Lichtenstein et al., 2006). Schools have been repeatedly regarded as (social) CAS, due to the fact that they comprise the aforementioned core characteristics of CAS (Snyder, 2013; Trombly, 2014). More specifically, they comprise a wide ecosystem of inter-related actors (e.g., teachers, leaders, students, parents, official accountability, infrastructural aspects), whose interactions and characteristics are combined into collective organizational system outcomes (Mital et al., 2014).

In this context, Complexity Leadership could also be applied for studying School Leadership in particular (Axelrod & Cohen, 2000; Morrison, 2010). **Complexity Leadership** posit the notion that strategic planning and outcomes are not solely devised by a single actor (*administrative leadership*), but are also the result of a range of actions and interactions from other system actors such as teachers (*adaptive leadership*) (Lichtenstein et al., 2006; Uhl-Bien et al., 2007). The *administrative leadership strand* is related to the "top-down" leadership processes, focusing on managerial aspects (Uhl-Bien et al., 2007). Examples of administrative leadership, which is usually performed by the principal leader, are strategic planning for the organization, allocation of resources and coordinating staff professional development activities (OECD, 2013c). The *adaptive leadership strand*, which is closely related to the distributed leadership standpoint, refers to the adaptive interactions of the school system actors (a key strand of which are the teacher leaders) that emerge from practice and not strictly as a result of authority (Uhl-Bien et al., 2007).

Utilizing both strands can offer higher levels of granularity for the leadership team in both (a) formulating more informed strategic school organizational plans, as well as (b) orchestrating the plans' realization. More specifically, the *formulation* of holistic strategic organizational plans can be enhanced by combining the feedback loops from the range of micro-layer educational data to which teachers have better access to with the meso/macro-layer school data which are available to principals (Day & Harris, 2002). The *orchestration* of the plans' realization can be more effectively performed within a more distributed, teacher-inclusive leadership model by allowing the leadership *team* to have a more detailed overview of the day-to-day progress and the potential shortcomings that occur within each institutional layer of the school (Mulford, 2003). Finally, despite an initial division of tasks among the two leader types (i.e., teacher leaders being mainly focused on micro/meso layer leadership and principal leaders being mainly focused on meso/macro layer leadership), there is an increasing trend towards blurring and intertwining the boundaries between each leader type's tasks (Firestone & Martinez, 2009). For example, teachers are assigned with tasks of managing staff professional development for their peers (Gonzales & Lambert, 2014) or principals are engaged with the design and/or orchestration of student learning activities (Copland & Knapp, 2006). It is becoming increasingly evident that effective and holistic school organizational development views both these leadership strands (administrative and adaptive) as complementary (OECD, 2008; OECD, 2013c; Bush & Glover, 2014). In order to allow for this complementarity, school complexity leadership is heavily reliant on formulating, sustaining and exploiting institution-wide mechanisms for collecting educational data among the actors of each organizational layer (Morrison, 2010). More specifically, collection of such data and actor interactions from an institution-wide perspective accommodates the need for and generates feedback loops for the current state of the school (e.g., student outcomes, teacher actions, parents' requirements, official accountability reports and policies).

Based on the above, this chapter adopts the conceptualization of school leaders as a dualistic concept, comprising the principal leader strand and the teacher leader strand (Leithwood et al., 2007; Crowther et al., 2009; OECD, 2008; OECD, 2013c). The following section builds on this conceptualization in order to present a set of core school leadership tasks, which will span the function areas of both leader strands.

3.2.1.2 School Complexity Leadership Tasks

As aforementioned, the complexity leadership approach requires school leaders to engage in a diverse set of tasks, which aim to monitor and orchestrate the full spectrum of the behaviours and interactions of school actors by collecting relevant feedback loops from institution-wide educational data (to be defined in Section 3.3), and effectively exploiting them in a holistic manner.

In order to define such school leadership tasks, and formulate a School Leadership Tasks framework (SLT), a review of scientific literature and widely accepted school leader standards from major global organizations was performed (see Table 7). This review focused on both strands of the adopted school leader concept. However, as stated before, such role distributions are not always strictly defined within schools and the tasks descriptions per leader strand are becoming increasingly blurred (Firestone & Martinez, 2009).

The review process highlighted a list of core school leadership tasks, which was post-processed towards grouping the semantically similar ones. This process resulted in a set of commonly referenced core school leader tasks, depicted in Table 1. More specifically, a set of 12 commonly referenced core leadership tasks was identified. However, "T12. Formulate Vision and Culture for Organizational Development" was not ultimately considered as a standalone leadership task in the chapter, since it is considered as an overarching task which affects and informs all the rest (Maslowski, 2006).

The remaining eleven core leadership tasks, which were utilized in this book chapter towards the formulation of the benchmarking SLT framework, are briefly outlined as follows:

- **Learning process monitoring (T1)**. This task relates to the monitoring of the learning processes that occur at the micro layer. Data types related to this leadership task can include (a) types of instructional practices and processes utilized and (b) (quantity and) method of utilized learning resources and tools.
- **Learning process evaluation (T2).** This task relates to the utilization of the data from the "Learning process monitoring (T1)" and their analysis towards remedying actions for improvement of the teaching and learning processes of the school. For example, this

can include an evaluation of the efficiency of the adopted instructional practices (and/or learning resources and tools) using the learners' academic performance, feedback and level of participation/engagement as a benchmark. A low level of the latter can assist school leaders to identify specific aspects of the teaching practice which were ineffective.

- **Learner performance monitoring (T3).** This task relates to data on learners' academic performance. These data can include among others, behavioural issues of the learners, absenteeism rates, level of participation within the learning activities and level/type of interactions with the teacher/leader or parents.
- **Learner performance evaluation (T4).** This task mainly relates to the assessment of the learners' academic performance based on the data collected from monitoring their progress and actions during the learning process (both within and beyond the physical premises of the school). This evaluation could be diagnostic, formative and/or summative and generate corresponding feedback loops.
- **Curriculum planning (T5).** This task relates to the identification of issues related to the existing curriculum and the actions towards remedy. These issues are mainly elicited from the feedback loops of the previous tasks and can relate either to shortcomings identified at a micro level (e.g., general difficulty of learners to cope with a specific curriculum section) or to externally imposed mandates (e.g., new subject domain standards).
- **Teaching staff management (T6).** This task relates to the monitoring and management of the teaching staff of the school in terms of both teaching performance (e.g., through the monitoring of the teaching processes and the related competences of the teachers) as well as operations (e.g., attendance, demographics and payroll).
- **Teaching staff professional development (T7).** This task relates to the identification of potential shortcomings in the teaching staff's competences and the organization and promotion of appropriate professional development opportunities to alleviate. Moreover, it can refer to the tasks of selecting and recruiting of new teaching staff, more appropriate for the school System needs.
- **District stakeholder accountability (T8).** This task relates to formulating and sustaining communication channels with interested stakeholders of the school in order to allow for capturing their own feedback loops towards capturing the level in which they affect the school system's level of emergence. Examples of such two-way feedback loops can include retention rate reports and financial reports of the school addressed at the policy makers, policy mandates from the policy makers to the school, as well as continuous two-way communication and collaboration between the teachers, students and the parents of the latter.

Table 7: Core School (Complexity) Leadership tasks

ID	Core School Leadership Task	Principal Leader								Teacher Leader / No distinction						
		Portin (2005)	Breiter & Light (2006)	Augustine et al. (2009)	Gill et al., (2014)	AITSL (2014)	BCPVPA (2013)	Earley (2012)	ISTE (2009)	Gill et al., (2014)	OECD (2008)	OECD (2014b)	Breiter & Light (2006)	CCSSO (2014)	TLEC (2010)	NEA (2014)
T1	Learning Process Monitoring	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
T2	Learning Process Evaluation	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
T3	Learner Performance Monitoring	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
T4	Learner Performance Evaluation		✓		✓	✓	✓	✓		✓	✓		✓	✓	✓	✓
T5	Curriculum Planning	✓	✓		✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓
T6	Teaching Staff Management (and Hiring)	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓		✓		
T7	Teaching staff Professional Development	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓
T8	District Stakeholder Accountability	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	✓	✓
T9	Infrastructural Resource Management	✓	✓	✓		✓	✓		✓		✓			✓	✓	
T10	Financial Resource Management		✓	✓	✓	✓	✓		✓	✓	✓			✓		
T11	Learner Data Management	✓	✓	✓		✓	✓	✓		✓	✓		✓	✓		✓
T12	Formulate Vision and Culture for Organizational Development			✓	✓	✓	✓	✓	✓		✓	✓		✓	✓	✓

- **Infrastructural resource management (T9).** This task relates to the management (e.g., monitor, maintenance, procurement) of the infrastructural assets of the school, such as hardware and software equipment.
- **Financial resource management (T10).** This task relates to the monitoring and orchestration of the financial aspects of the school, such as budget formulation, accounting tasks and external funding.
- **Learner data management (T11).** This task relates to the overall management of learners' data, such as demographics, tuition fees and prior academic background. Apart from the strictly administrative need for record keeping, such data types (which, like staff management, are related to the characteristics of a set of school actors) can be exploited as a means to explain the interactions of these actors with the rest of the system. Therefore, this information can facilitate in the (at least partial) understanding of the current level of system emergence.

Within the context of complexity leadership, the proposed SLT attempts to capture the core aspects of school functions which are affected by administrative leadership, but also nurture the emergent adaptive leadership. More specifically, the formulated SLT Framework describes commonly recognized aspects of school function that are orchestrated by the school leadership team and include a wider range of school System actors (e.g., parents, external accountability bodies and the students). The identified school leadership tasks are mainly related to capturing and monitoring these aspects by receiving constant flows of feedback loops from institution-wide educational data. Therefore, mechanisms for effective collection, analysis and exploitation of institution-wide data are required, towards generating evidence-based and highly granulated feedback loops. This data-driven decision making process is described in the following section in terms of conceptual underpinning and data type requirements in the context of school complexity leadership.

3.2.2 Data Driven Decision Making

Data-driven decision making (DDDM) in Education has received an increasing level of attention, on a global scale (Lai & Schildkamp, 2013). The reason for the emerging focus on DDDM is that apart from a well-established means for external regulatory accountability, is also identified as a driver of internal school improvement processes (Mourshed et al. 2010; Mandinach, 2012; Dunn et al., 2013). More specifically, DDDM is directly related to the mechanisms for capturing and exploiting feedback loops from the multi-layer educational data (i.e., characteristics and interactions of the school System actors) towards attempting to increase the transparency of the processes that formulate each status of the school System emergence.

Towards outlining the concept of DDDM, Table 8 presents an overview of common definitions. As the Table 8 depicts, all definitions (despite their diversity in the adopted level of detail) share a common core notion, namely that DDDM refers to the collection, analysis, and interpretation of institution-wide data towards generating feedback loops and insights for informing leadership in educational settings (Mandinach, 2012). Therefore, data from the micro/meso layers should be harvested and processed in order to unravel the classroom "black box", and data from the macro layer should be analyzed and utilized in order to inform the organizational development of the school and its strategic planning. This cyclical process comprises an initial stage of data collection, followed by the stage of analytical process and transformation of these data towards the formulation of feedback loops, and the resulting stage of the provision of actionable insights (Mandinach, 2012).

Table 8: Definitions of School Data driven Decision Making

#	Source	Definition
1	Dahlkemper (2002)	DDDM is the process of collecting, analyzing, reporting, and using data for school improvement
2	Doyle (2003)	DDDM is the process of collecting student data –academic performance, attendance, demographics, etc- in such a way that administrators, teachers and parents, can accurately assess student learning
3	Crawford et al. (2008)	DDDM relates to policies and practices involving the use of student achievement and other data (such as attendance, coursetaking patterns and grades, and demographic data) to drive school improvement at the school, district, and state levels.
4	Mandinach (2012)	DDDM is the systematic collection, analysis, examination, and interpretation of data to inform practice and policy in educational settings
5	Schildkamp & Kuiper (2010)	DDDM refers to systematically analysing existing data sources within the school, applying outcomes of analyses to innovate teaching, curricula, and school performance, and implementing and evaluating these innovations
6	Dunn et al. (2013)	DDDM refers to the systematic collection of many forms of data from a multitude of sources in order to enhance student performance

7	Marsh & Farrell (2014)	DDDM refers to teachers, principals, and administrators systematically collecting and analyzing various types of data [...] to guide a range of decisions to help improve the success of students and schools

As aforementioned, the data harvested during the DDDM process should originate from all layers of the institution and reflect a wide range of the schools' factors and practices. This will allow school leaders to gain insights from a holistic perspective and, thus, enable them to make more informed decisions (Earl & Katz, 2006). However, given the evident diversity of these data types and sources, an efficient way should be adopted to classify and organize them towards the formulation of a School Leadership Task framework (SLT) as discussed in Section 3.2.1.2.

A widely accepted data type classification framework defines four main data categories, as follows (Stufflebeam & Shinkfield, 2007; Ikemoto & Marsh, 2007; Schildkamp et al., 2014):

- **Input data**. This category generally includes data related to learner demographics and learners' prior academic records. Furthermore, it can also include data on teachers' characteristics, such as competences, expertise and qualifications.
- **Process data**. This category refers to data generated during the teaching and learning process, such as the types and use of learning resources, teaching staff performance and student competence monitoring,
- **Context data.** This category refers to data related to the curriculum, the infrastructural, financial and human resources aspects of the school as well as data on the collaboration with other actors of the school system, such as the parents, official policy and other schools.
- **Outcome data**. This category mainly refers to data on learner academic achievement (e.g., assessment results) and retention data.

Following the above-mentioned classification framework, a set of commonly utilized data types in school leadership DDDM processes was identified and is presented in Table 9 (Marsh et al., 2006; Breiter & Light, 2006; Picciano, 2009; Copland et al., 2009; Means et al., 2010; Schildkamp & Ehren, 2013; Lai & Schildkamp, 2013; Murray, 2013; Kaufman et al., 2014; Gill et al., 2014; Schildkamp et al., 2014).

Table 9: Commonly utilized data types for school leadership data driven decision making

#	Data Category	Data Type	Indicative Example	Institutional Layer
1	Input Data	Learner demographics	Demographics reports	Macro
2		Learner prior academic performance	Prior academic performance records	Macro
3	Process Data	Learner attendance	Attendance reports	Micro
4		Learner behavior	Behavior history report	Micro
5		Use of learning resources	Type of educational resources utilized	Micro / Meso
6	Process / Context Data	Learning process monitoring data	Teaching method utilized	Micro/ Meso
7	Context Data	School financial data	School budget	Macro
8		School infrastructural data	School (hard)/ (soft) ware inventory	Macro
9		Teaching staff monitoring	Attendance, payroll, competences	Meso/ Macro
10		Stakeholder evaluation data	Parent feedback	Macro
11	Outcome Data	Learner assessment results	Disaggregated / Aggregated learner assessment results	Macro
12		Learner retention rates	Graduation reports	Macro

As the Table 9 depicts, the set of commonly identified institution-wide data required for DDDM processes spans both micro and meso institutional layers and is significantly diverse and complex in order to offer effective decision support for school leaders.

3.3 Proposed Holistic Data-driven School Leadership Framework

By combining and mapping the identified institution-wide data types that inform school leadership DDDM (Table 9) to the set of the eleven core school leadership tasks (Table 7), a school leadership task framework (SLT) is formulated and presented in Table 10. It essentially describes the core school leadership tasks and the specific institution-wide data types which support each of them. The SLT will be utilized for critically reviewing a set of existing school leadership decision support systems (Section 3.4).

Table 10: School Leadership Task framework

ID	Core School Leadership Task	Indicative Data Types
T1	Learning Process Monitoring	• Use of learning resources • Learning process monitoring data
T2	Learning process Evaluation	• Use of learning resources • Learning process monitoring data • Learner assessment results
T3	Learner Performance Monitoring	• Learner attendance • Learner behavior
T4	Learner Performance Evaluation	• Learner assessment results • Learner attendance • Learner behavior
T5	Curriculum Planning	• Learning process monitoring data • Learner assessment results
T6	Teaching Staff Management	• Learner assessment results • Learning process monitoring data • School staff monitoring
T7	Teaching staff Professional Development	
T8	District Stakeholder Accountability	• Stakeholder evaluation data • Learner assessment results • Learner retention rates
T9	Infrastructural Resource Management	• School infrastructural data
T10	Financial Resource Management	• School financial data

T11	Learner Data Management	• Learner demographics • Learner prior academic performance • Learner attendance • Learner behavior

However, such level of granulated data is usually difficult to attain (especially at a micro/meso layer) and is also delivered with significant time delay, thus impeding the capacity of leaders to identify issues to be tackled and act on-the-fly (Marsh et al., 2006; Ikemoto & Marsh, 2007). Moreover, data are not informative on their own but require processing and analysis in order to make sense of them and utilize them for supporting the corresponding leadership task (Marsh et al.,2006; Coburn & Turner, 2011). Under the light of the above, the capacity of school leaders to perform their required tasks effectively and efficiently is directly linked to the level of availability and quality of the institution-wide data and their meaningful analysis (Mandinach, 2012). In addition to this, school leaders have been reported with competence-related difficulties in analyzing the available institution-wide data and exploiting them towards delineation of actionable insights (Lai & Hsiao, 2014; Marsh & Farrell, 2014).

In order to address the abovementioned issues that tend to impede the holistic data driven leadership of schools, decision support systems have been implemented, that harvest and analyze the available data, towards the generation of feedback loops and actionable insights (Power, 2008a; Kaufman et al., 2014). More specifically, decision support systems (in general, and in the context of school leadership) can afford, among others, timely harvesting and processing of data towards effective action-taking (Pick, 2008), user-friendly and elaborate visualizations towards clear sense-making (Mottus et al., 2015) and data aggregation mechanisms to address multi-criteria problems (Breiter & Light, 2006; Olson, 2008). Despite their promise, however, decision support systems, and more specifically school leadership decision support systems (SL-DSS), have not yet reached their full potential to robustly support all tasks required for holistic school DDDM (Kaufman et al., 2014).

Under the light of the above, a critical analysis of 70 existing SL-DSS was performed. More specifically, considering that SL-DSS aim to facilitate school leaders in engaging with their tasks, the issue of critically analyzing SL-DSS can be summarized as assessing the level of accommodation that the SL-DSS affordances offer in terms of the identified school leader tasks, described in the SLT. Therefore, this critical analysis of the landscape of SL-DSS could highlight potential shortcomings in terms of the affordances of these systems to adequately accommodate each school leadership task described in the SLT. The insights gained from this process could lead to recommendations for designing future SL-DSS, which will provide more holistic support to school leaders. The following section presents the critical analysis methodology and results.

3.4 Critical Analysis of School Leadership Decision Support Systems

3.4.1 Critical Analysis Methodology

A technical affordances-focused approach was selected for driving the critical analysis process, i.e., the selected SL-DSS were assessed solely on the premises of their functionalities' capacity to accommodate the benchmarking SLT framework (Power, 2008b; Rhee & Rao, 2008). Other assessment methods, such as subjective measures (e.g., user satisfaction or perceived efficiency of the decision support system) were not considered in this process.

Regarding the selection criteria utilized for formulating the list of SL-DSS to be analyzed, a threefold set was utilized, namely (a) the SL-DSS should be an standalone, already deployed system, i.e., not simply a design or an add-on to existing systems (therefore mainly commercial SL-DSS were identified), (b) the SL-DSS should be addressed at the K-12 school context and (c) the SL-DSS should incorporate mechanisms for *actively* supporting leadership tasks (i.e., not simply harvest institution-wide data, but also utilize them towards the provision of feedback loops and actionable insights). Adhering to these three selection criteria, a set of 70 existing SL-DSS were identified via web search using the Google search engine (see Appendix for full list).

Finally, regarding the procedure of the critical analysis (i.e, the steps taken for assessing each SL-DSS), it comprised assessing each SL-DSS in terms of the cardinality of core leadership tasks (i.e., elements of the SLT) it afforded support for. Moreover, the institution-wide data types it harvested and exploited was also taken into consideration as a means of "validation", i.e., to verify that the stated core leadership task which was mentioned by the system as being supported, was indeed supported. Ultimately, the aggregated insights gained from this process could outline recommendations for the design and deployment of future SL-DSS that will provide school leaders with more holistic support in managing the organizational learning processes of their schools. The results of the critical analysis are presented in the following section.

3.4.2 Critical Analysis Results

Table 11 presents the critical analysis of 70 existing SL-DSS, based on the SLT framework.

Table 11: Critical Analysis of school leadership decision support systems

ID	School Leadership Task	School Leadership Decision Support System ID*
T1	Learning Process Monitoring	[1], [2], [3], [4], [5], [6], [7], [9], [10], [11], [12], [13], [14], [21], [22], [23], [24], [25], [28], [29], [32], [35], [36], [39], [43], [44], [45], [49], [50], [51], [52], [53], [57], [60], [61], [64], [65], [67], [69], [70]
T2	Learning process Evaluation	[3], [4], [7], [9], [10], [11], [12], [13], [14], [21] , [22], [23], [24], [28], [29], [32], [43], [44], [45], [47], [49], [51], [52], [53], [57], [60], [61], [64], [65], [67]
T3	Learner Performance Monitoring	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [42], [43], [44], [45], [46], [47], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [69], [70]
T4	Learner Performance Evaluation	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [12], [13], [14], [16], [17], [19], [21], [22], [23], [24], [25], [26], [27], [28], [29], [32], [34], [35], [36], [37], [39], [43], [44], [45], [46], [47], [49], [50], [51], [52], [53], [54], [55], [57], [58], [59], [60], [61], [62], [63], [64], [65], [67], [69], [70]
T5	Curriculum Planning	[3], [4], [7], [9], [11], [12], [13], [14], [21], [22], [23], [24], [28], [29], [32], [37], [43], [44], [45], [47], [49], [51], [52], [53], [57], [60], [61], [63], [64], [65], [67], [69], [70]
T6	Teaching Staff Management	[2], [3], [5], [6], [7], [9], [11], [12], [13], [15], [17], [18], [20], [22], [24], [28], [29], [32], [33], [34], [36], [37], [38], [40], [43], [44], [45], [46], [47], [48], [49], [51], [52], [53], [54], [55], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [68], [69]
T7	Teaching Staff Professional Development	[2], [7], [9], [11], [12], [13], [17], [18], [20], [21], [23], [24], [28], [29], [32], [34], [36], [37], [40], [44], [47], [48], [49], [51], [52], [53], [54], [57], [64], [68], [69]
T8	District Stakeholder Accountability	[1], [2], [3], [4], [5], [6], [7], [9], [10], [11], [13], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [42], [43], [44], [45], [46], [47], [49], [50], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [63], [64], [65], [66], [67], [69]
T9	Infrastructural Resource Management	[2], [9], [18], [22], [33], [36], [38], [41], [45], [46], [48], [49], [52], [55], [57], [58], [61], [62]

T10	Financial Resource Management	[2], [3], [4], [7], [9], [12], [13], [18], [20], [22], [26], [31], [33], [34], [36], [41], [44], [45], [46], [48], [49], [52], [62], [66], [69], [70]
T11	Learner Data Management	[1], [2], [3], [4], [5], [6], [7], [8], [9], [10], [12], [13], [15], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [42], [43], [44], [46], [47], [48], [49], [50], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66], [67], [69], [70]

** The " School Leadership Decision Support System ID " is defined in the Appendix*

Figure 5 presents the consolidated critical analysis results on the level of accommodation that each leadership task is receiving from existing SL-DDS.

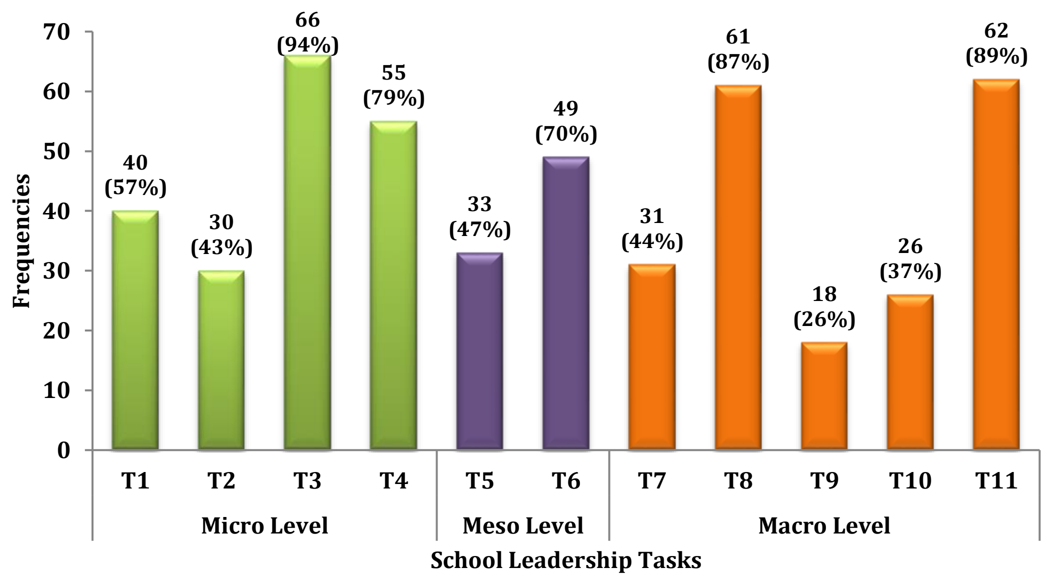

Figure 5: Frequencies of SL-DSS supporting each school leadership task

As the Figure 5 depicts, the consolidated overview of the existing SL-DSS highlights a set of key findings, which are described as follows:

- The leadership tasks receiving the highest level of accommodation are "*T3. Learner Performance Monitoring*" (N= 66, x=94%), "*T4. Learner Performance Evaluation*" (N= 55, x=79%), "*T8. District Stakeholder Accountability*" (N= 61, x=87%) and "*T11. Learner Data Management*" (N=62, x=89%). This finding mirrors the common notion that school leadership is heavily influenced and driven from the external regulatory accountability mandates, either officially from policy-makers or unofficially from parents and other schools. Under this light, SL-DSS have placed a significant level of attention in assisting leaders to effectively capture, monitor and enhance learner performance (mainly through assessment results and attendance rates) to meet these accountability goals. The majority of existing SL-DSS also aim to facilitate leaders in reporting these learner performance data to the interested stakeholders, by providing aggregation and report formulation functionalities.

- The leadership tasks receiving the lowest level of accommodation are "*T9. Infrastructural Resource Management*" (N= 18, x=26%) and "*T10. Financial Resource Management*" (N= 26, x=37%). These types of macro layer tasks, therefore, appear to be under-supported (from an aggregated view) from SL-DSS and, therefore, their interrelation with other institution-wide data towards holistic decision support is not widely provided. However, this can prove to be an important shortcoming, since the quality, availability and quantity of both school infrastructure (e.g., OECD, 2011) as well as school financial resources (e.g., Nachmias et al., 2004) can greatly affect the teaching and learning processes of the micro/meso layers. Therefore, more attention should be provided to support these leadership tasks, in order to facilitate more holistic school management.
- The leadership tasks "*T6. Teaching Staff Management*" (N= 49, x=70%) and "*T7. Teaching Staff Professional Development*" (N=31, x=44%) appear to be considered as important by a significant portion of the SL-DSS (especially task T6), which provide decision support affordances for supporting them. More specifically, most teaching staff management affordances refer to teaching staff demographics, attendance, pay-roll, as well as recruitment facilitation. The teaching staff professional development affordances are generally related to the cultivation of professional learning communities and (in cases of formal professional development), tracking of the progress of the teachers towards completion. Future SL-DSS could focus more on the aspect of promoting targeted teacher professional development, considering data collected from the micro/meso layer and the insights these could yield concerning the competences of the teacher. The latter could be measured through official teacher competence frameworks (such as the UNESCO ICT Competency Framework for teachers (UNESCO, 2011) or Technological Pedagogical Content Knowledge (TPACK, Koehler & Mishra, 2009)), and be mapped to professional development courses which will

cultivate the specific competences that each teacher is lacking (Sergis et al., 2014a [P2]; 2014b [P7]).

- Finally, the micro layer leadership tasks "*T1. Learning Process Monitoring*" (N= 40, x=57%) and "*T2. Learning process Evaluation*" (N= 30, x=43%), have received a moderate level of accommodation. The latter poses an interesting finding, since these tasks are required for facilitating teacher's reflection and development towards enhancing learners' performance (OECD, 2009; Vieluf et al., 2013). This fact is also mirrored in the low level of accommodation that the meso layer leadership task "*T5. Curriculum Planning*" is receiving (N= 33, x=47%). More specifically, data collected in T1 and T2 (including types of learning resources utilized, the level of their usage, and the type/diversity of instructional methods and practices employed by the teacher) can provide a wealth of information for the targeted identification of the roots for issues underlying other leadership tasks (i.e., T3, T4, T5, T7 and T11). Therefore, this limited accommodation from SL-DSS is deemed as significant and supports the finding that existing SL-DSS seem to place much attention in monitoring learners' performance and retention from a clear external regulatory accountability perspective.

In the light of the last finding, an additional level of qualitative meta-analysis was performed for "*T1. Learning Process Monitoring*", towards gaining a more detailed insight of the exact level of accommodation that each data types that feed this task are receiving (based on the analysis of Section 2.2). The meta-analysis process highlighted that the data type "*T1a. Types and level of usage of learning resources utilized*" is universally accommodated by the portion of SL-DSS which support the leadership task T1. On the other hand, a surprisingly low portion of 13 SL-DSS (x=32% of the SL-DSS portion supporting task T1, and x=19% of the overall 70 SL-DSS) harvest data related to the actual methods and practices that the teachers utilize in their classrooms, i.e. data type "*T1b. Instructional methods and practices employed*". Despite the widely accepted notion that teaching methods directly influence the level of learners' outcomes (as well as level of engagement, motivation etc), the majority of existing SL-DSS does not explicitly accommodate collection of such data to inform school leadership towards remedying for potential shortcomings in terms of the teaching practices being employed in the micro(/meso) layer. Moreover, the performed analysis indicated that even the small portion of them that do harvest such data (x=19% of the overall 70 SL-DSS), do not link them to the other institution-wide data collected (such as learner performance, learner retention rates and teacher competences) towards holistic assessment of the teaching practices and leader reflection.

The abovementioned situation highlights that making transparent the "black box" of the classroom is apparently not yet widely achieved and targeted at. Moreover, this supports the notion that the main scope of external regulatory accountability is still (to a large extend) focused at monitoring the quantitative data of learners' assessment results and retention rates, rather than the quality and appropriateness of the teaching practices that take place in the classrooms (Knapp & Feldman, 2012; Gonzalez & Firestone, 2013). However, it is the latter which holds the greatest promise towards school improvement since it can directly influence (and be influenced by) all other leadership tasks from learner performance and teacher professional development to management and procurement of required infrastructural assets (Cranston, 2013). Therefore, the very limited level of accommodation from existing SL-DSS on these data types (and corresponding core leadership tasks) is an important shortcoming. Additionally, given the emerging trend of external accountability beyond mere quantitative assessment measures towards qualitative performance-based evaluations of schools, supporting school leaders in effectively capturing and monitoring the teaching processes of their school will likely become a major requirement for future SL-DSS (Altrichter & Kemethofer, 2015).

Finally, besides external accountability (to both policymakers and parents) these micro/meso layer data can be of great value in terms of providing evidence to the overall teaching community to support (or oppose) best practices of teaching in particular contexts. More specifically, utilizing the currently harvested wealth of other institution-wide data types (e.g., learner demographics and school infrastructure), future SL-DSS could formulate a detailed learning contextual framework (i.e., the learning environment), in which different teaching approaches could be tested and reflected upon, using the learner outcomes as a benchmarking means. By doing that, evidence on the best practices could be gathered, since both the "black box" of the classroom as well as the context of the school in which the teaching practice is being performed, would be linked to the teaching process and the resulting learner outcomes. Therefore, each teaching practice could be evaluated based on not only the static description of its components (e.g., educational objectives, learning activities, educational resources and tools), but also based on a highly-granulated representation of (a) the context in which the practice was executed and (b) the outcomes it delivered on the learners. Afterwards, these pools of teaching practices (with all their aforementioned detailed meta-information) could be shared through web-based repositories, in which school teachers could identify the "best teaching practices" for their needs, based on their own institution's and classroom's contextual information.

3.5 Conclusions

The global push towards school autonomy and accountability has assigned school leaders with a diverse and complex set of tasks towards meeting organizational goals, as well as delivering high levels of quality in terms of actual learning outcomes for their students. Engaging with these tasks requires harvesting and processing a diverse set of institution-wide data. To effectively address this issue, school leadership decision support systems are deployed.

This chapter proposed a holistic SLT with the aim of depicting the range of decision making tasks that school leaders are engaged with. Furthermore, a critical analysis of a set of 70 SL-DSS was also performed in order to identify existing shortcomings and to pinpoint potential areas of future development. The results of the critical analysis highlighted that the clear majority of identified SL-DSS specifically focused on assisting school leaders cope with the externally mandated regulatory accountability requirements in terms of monitoring, enhancing and reporting students' summative assessment score data and/or retention rates. On the other hand, macro layer "business" managerial tasks such as the management and strategic orchestration of the schools' finances and infrastructure have received much less attention, potentially hindering the capacity of leaders to include such information in their holistic planning.

Additionally, a significant shortcoming of existing SL-DSS relates to the limited quantitative and qualitative accommodation of micro and meso layer data that could inform meaningful internal school improvement (as well as qualitative performance-based external accountability). Examples of such data are the monitoring and reflective evaluation of the teaching practices employed by the teachers. Specific focus should be placed on this aspect, however, based on both the emerging trends of qualitative external accountability, which will most likely require such data to be harvested and presented in the future, as well as the significant added value it can offer in terms of promoting the teaching profession and formulating pools of teaching practices (e.g., educational scenarios or lesson plans) which will not only present the "static design" of this practice, but will also attach to it the specific contextual parameters in which the practice was performed and the learner outcomes it produced within this specific context of execution.

Capitalizing on the outcomes and insights, the following chapter delves deeper in the field of data-driven decision making for school leadership, by investigating and discussing how existing Data Analytics methods have (and could) be used in order to support evidence-based school leadership. Furthermore, shortcomings of existing Analytics approaches are discussed, and a proposal is made for more holistic *School Analytics* methods.

4 School Analytics: An Analytics framework to support holistic data-driven School Leadership

4.1 Introduction

As discussed in the previous chapter, data-driven decision making (DDDM) in Education has received an increasing level of attention, on a global scale (Lai & Schildkamp, 2013). Employing data-driven decision making processes, or *Analytics* as it is usually referred to (Ravishanker, 2011; van Barneveld et al., 2012), is considered to be instrumental towards effective organizational complexity leadership, since it can provide a solid basis for formulating and sustaining essential interaction and communication channels within the school system actors (Uhl-Bien et al., 2007; Lai & Schildkamp, 2013; Pistilli et al., 2014). These channels provide continuous feedback loops to these actors (and the leadership team in particular) and are at the core of sustainable School Complexity Leadership by enabling and monitoring the *emergence* of the system – that is to say, the current status of the system, which is not a linear sum of its constituent parts but has been forged in a networked and unpredictable manner by the characteristics and interactions of its actors (Uhl-Bien & Marion, 2009). As a result, the research community has been striving towards identifying effective analytics methods for supporting leadership decision making through the collection and exploitation of institution-wide data (e.g., Cosic et al., 2012).

Towards addressing the aforementioned goal in an *educational context*, the concept of Analytics has spawned two core strands, namely *Learning Analytics* (LA) and *Academic Analytics* (AA) (Long & Siemens, 2011; Norris & Baer, 2013; Ferreira & Andrade, 2014). *Learning Analytics* are addressed to all types of educational institutions (e.g., K-12 schools and Higher Education Institutions – HEI), as well as online education (e.g., Massive Open Online Courses - MOOCs), and mainly aim at providing data-driven decision support for the micro/meso-layers (Long & Siemens, 2011). Academic Analytics, on the other hand, are specifically addressed to HEI and mainly aim at providing data-driven decision support on a macro-layer related to the Business Intelligence of the organization (Siemens, 2013; Daniel, 2015). A new Analytics strand is also emerging in the context of education, namely *Teaching Analytics*, which aim to provide analysis and evaluation of the teaching practices of a school. More commonly, they refer to methods and tools that enable teachers (or instructional designers) to analyse their designs in order to better reflect on them (as a whole or elements of them. Even though this Analytics strand is gaining attention, especially when combined with

Learning Analytics to support teacher reflection and improvement (Sergis & Sampson, 2017), it is still a young field and is not directly addressed in this chapter.

Despite the increased research and industry attention placed on the two major Analytics strands, the existing approaches do not appear to be able to adequately support the specific needs of K-12 school complexity leadership. This hypothesis is based on the fact that K-12 school leaders require *holistic* data driven decision support in order to effectively engage with their complex tasks, given the ecosystemic nature of schools as social complex adaptive systems (Huang & Kapur, 2012; Sergis & Sampson, 2014a; Trombly, 2014). More specifically, as aforementioned in the previous chapter, these tasks require highly granulated data collection and processing from all school layers (that is, micro, meso and macro) towards generating continuous feedback loops and communication channels. The latter two that can be exploited by school leaders for driving systemic school development and monitoring the state of the schools' emergence towards strategic insights (Miller & Page, 2007; McQuillan, 2008). In addition to this, school autonomy and accountability are being globally pursued and promoted, thus assigning school leaders with higher levels of responsibility than before (Hooge et al., 2012). Lastly, school leaders' decision making capabilities are hindered by the fact that existing decision support systems have not yet reached their full potential to support the full spectrum of school leaders' tasks (Kaufman et al., 2014; Sergis & Sampson, 2016a [**P4**]).

Under the light of the above, it becomes evident that the two existing analytics strands do not offer the capacity for the *holistic* decision support required by K-12 school complexity leadership, given their isolated focal points and leadership objectives. Therefore, this chapter proposes a new educational analytics framework, namely *School Analytics* which aims at tackling this shortcoming and, thus, facilitate K-12 school complexity leadership. School Analytics are presented as a holistic multi-level analytics framework aiming to integrate and analyze "Business Intelligence" (macro-layer) data and Educational/Learning (micro/meso-layer) data in an intertwining manner towards the provision of more granulated feedback loops to the school leadership. These feedback loops, which require highly granulated and continuous mechanisms for capturing, analyzing and exploiting institution-wide educational data, can allow for the school leaders to monitor and (partially) influence the emergence states of their school towards meeting the needs of the school system actors (e.g., students, teachers, parents, external policy mandates).

The remainder of the chapter is as follows. Section 4.2 defines the background of this work, namely the definitions and main objectives and methods of analysis of Academic Analytics and

Learning Analytics. Additionally, for each analytics strand, a review of indicative existing systems is performed towards identifying the level of accommodation provided for their respective objectives. Section 4.3 presents the background of school complexity leadership and the proposed School Analytics concept in terms of focal points and objectives towards facilitating K-12 school complexity leadership data driven decision making. Moreover, potential implications of the School Analytics are discussed in towards the design of systems offering systemic school leadership support affordances. Finally, Section 4.4 presents the conclusions drawn.

4.2 Background

The following subsections describe the two core educational Analytics strands, namely Academic Analytics (AA) and Learning Analytics (LA). Each of the two strands are analyzed in terms of focal points and key leadership objectives they aim at supporting, through the provision and exploitation of data generated in all layers of educational institutions

4.2.1 Academic Analytics

4.2.1.1 Academic Analytics: Definition

Academic Analytics refer to data-driven decision making practices for informing operational purposes at the Higher Education level (Baepler & Murdoch, 2010). Academic Analytics are addressed at providing HEI leaders with support for managing the processes of the macro institutional layer, namely the "Business Intelligence" (Goldstein & Katz, 2005; Elias, 2011; Chatti et al., 2012; Siemens, 2013). These processes primarily refer to operational and financial decision making (van Barneveld et al., 2012; Ferreira & Andrade, 2014). A similar term used in the literature is that of Action Analytics which considers similar data and decisions at a macro-layer towards the generation of informed insights (Norris et al., 2009). For the context of this chapter, the term Academic Analytics will also incorporate Action Analytics. Therefore, existing Academic Analytics approaches are directly linked to orchestrating organizational processes such as student admission and management, finance and fundraising, faculty management and infrastructure procurement (Goldstein & Katz, 2005; Siemens et al., 2011; Chatti et al., 2012; Macfadyen & Dawson, 2012; Daniel, 2015).

4.2.1.2 Academic Analytics: Methods and objectives

Academic Analytics approaches have largely relied on specific data analysis methods, namely data mining, statistical analysis and predictive modeling (Campbell et al., 2007; Baepler & Murdoch, 2010; Daniel, 2015). These analysis methods have been primarily exploited in order to address a set of core objectives of Academic Analytics, mainly focusing on the macro-layer tasks of the HEI. This set of core Academic Analytics objectives is presented below, in terms of general description, required data types, as well as the purpose for which they are being pursued:

- **AA–O1. Student Management.** This objective relates to the facilitation of HEI leadership to manage the diverse set of student data.
  Common data types utilized are:
  - demographic data (Campbell et al., 2007),
  - admission and past academic records (Goldstein & Katz, 2005; Antons & Maltz, 2006; Bohannon, 2007),
  - course enrollment status (Pirani & Albrecht, 2005; Ravishanker, 2011; bin Mat et al., 2013) and
  - grants administered (Antons & Maltz, 2006; Norris et al., 2008).

  Main Purpose. Apart from the evident need of HEI leadership to keep track of their student's data, Academic Analytics have moved beyond mere capturing of these data towards providing insights. Regarding student admissions in particular, Academic Analytics can offer informed predictive recommendations on the best student candidates, based on their previous academic performance and standardized test results (Campbell & Oblinger, 2007; Vialardi et al., 2011; Bichsel, 2012). Additionally, Academic Analytics have utilized predictive modeling techniques in order to predict future admission and enrolment rates, towards strategically allocating available resources (Campbell et al., 2007; Norris et al., 2008).
- **AA–O2. Infrastructure management.** This objective refers to the management of the available infrastructure and the provision of insights for targeted maintenance and/or update (Goldstein & Katz, 2005).
  Common data types utilized are:
  - the quantity and quality of physical and digital resources, such as IT equipment (Campbell & Oblinger, 2007) and library resources (Bichsel, 2012).

- the aggregated level of usage of these resources (Campbell & Oblinger, 2007; Bichsel, 2012).

Main Purpose. An evident purpose to oversee the quality of the HEI infrastructure relates to the need to monitor availability and identify needs, such as to replace or update potentially "out-of-order" resources, either physical (e.g., computers) or digital (e.g., the HEI Learning Management System). Apart from this, these data can also be utilized in conjunction with other HEI function areas and provide insights such as delineating more efficient admission and enrolment plans in order to optimize resource allocations (Campbell et al., 2007; Long & Siemens, 2011).

- **AA–O3. Faculty management.** This objective primarily relates to facilitating HEI leadership to oversee and potentially support faculty in terms of performance, i.e., research and teaching (Bichsel, 2012).
  Common data types utilized are:
  - faculty demographic data (Dziuban et al., 2012)
  - quality and quantity of research conducted (Campbell & Oblinger, 2007; Long & Siemens, 2011), and
  - student academic performance and course enrollment as an indicator for evaluating teaching performance (Pirani & Albrecht, 2005; Dziuban et al., 2012; Howlin & Lynch, 2014).

  Main Purpose. Apart from the evident rationale of internal HEI management and improvement (including, faculty professional development and hiring), exploitation of the aforementioned data can be crucial for the HEI in terms of meeting external accountability goals (Ferreira & Andrade, 2014; Gašević et al., 2015). Therefore, HEI leadership can utilize the insights generated towards remedying actions, such as targeted curriculum (or course) improvements (Bichsel, 2012).
- **AA–O4. Financial management.** This objective mainly aims to provide decision support for orchestrating the financial action plan (Pirani & Albrecht, 2005; Long & Siemens, 2011; Bichsel, 2012).
  Common data types utilized are:
  - students' tuition fees and grants (Forsythe et al., 2012; Barber & Sharkey, 2012; bin Mat et al., 2013),
  - faculty related costs, such as salary, professional development costs and research funds (Campbell & Oblinger, 2007)

- infrastructure maintenance and procurement costs (Campbell & Oblinger, 2007) and
- external alumni or sponsor fundraising (Bohannon, 2007; Bichsel, 2012).

Main Purpose. The main purposes driving the harvesting and exploitation of the abovementioned data types include:

- the provision of alerts when the financial plan of the organization side-tracks (Goldstein, 2005),
- utilization of these data in conjunction with other HEI function areas, such as enrolment prediction and optimal resource allocation (Bohannon, 2007; Norris et al., 2008; Bichsel, 2012; Forsythe et al., 2012)
- facilitation of HEI leadership to identify sources of external sponsorship with a higher possibility to donate funds to the organization using predictive modeling techniques (Campbell et al., 2007).

- **AA–O5. Student retention.** One of the most common objectives of Academic Analytics is the monitoring of the student retention rates and the provision of decision support to HEI leadership towards remedying actions, in case of low such levels (Campbell & Oblinger, 2007; Taylor & McAleese, 2012; Lauría et al., 2012). More specifically, by utilizing data mining and predictive modeling techniques, Academic Analytics can process a wide range of student data towards predicting the possibility of each student to drop out from a course (Macfadyen & Dawson, 2010; Arnold, 2010; Smith et al., 2012; bin Mat et al., 2013).
Common data types utilized are:

- student demographics (Jayaprakash et al., 2014),
- student financial data, including grants provided and prior financial capacity (Barber and Sharkey, 2012),
- assessment results (Baepler & Murdoch, 2010; Jayaprakash et al., 2014),
- level of engagement in learning activities (Arnold, 2010; Phillips et al., 2010; Graf et al., 2011)
- prior academic performance (Ice et al., 2012)

Main Purpose. Mining, analyzing and visualizing the abovementioned data types can facilitate HEI leadership by:

- generating "early alerts" for students that appear to be lagging in terms of their academic performance and to provide warnings that will potentially lead to remedying actions (Norris et al., 2008; Baepler & Murdoch, 2010; Frankfort et al., 2012; Arnold & Pistilli, 2012; Howlin & Lynch, 2014)

  - providing correlations between students' performance to groups of students from other cohorts to highlight potential shortcomings (Baepler & Murdoch, 2010; Jayaprakash et al., 2014)
  - generating recommendations of more appropriate educational pathways can also be provided to the students and student tutors (Vialardi et al., 2011; Bramucci & Gaston, 2012)
  - facilitating the process of curriculum re-structuring to address common student performance problems (Bichsel, 2012; Howlin & Lynch, 2014; Daniel, 2015).

Finally, the above data analyses can assist HEI leadership to meet the institution's internal improvement plan (Campbell & Oblinger, 2007), as well as its external accountability goals (Ice et al., 2012; Bahr, 2012; Norris & Baer, 2013).

The analysis of key objectives of Academic Analytics supports the initial statement that, apart from its explicit focus on HEI, existing Academic Analytics approaches have focused on orchestrating the Business Intelligence of the macro organizational layer. This can be (at least partly) attributed to the common mandates regarding external accountability, which mainly include (a) reporting the level of quality of operations to policy makers and funders (Norris et al., 2009; Ferreira & Andrade, 2014; Gašević et al., 2015) and (b) achieving high rankings in inter-HEI benchmarks which are largely based on a diverse set of data (e.g., staff-to-student ratio, research quality/quantity, resource allocation per student, alumni professional success) (Siemens, 2013; Daniel, 2015). On the other hand, explicit orchestration of the teaching and learning processes of the micro/meso-layers of the HEI is not robustly addressed and supported by Academic Analytics approaches.

Table 12 provides a consolidated overview of the above analysis of Academic Analytics objectives, towards:

- supporting section 4.2.3.1, which presents an analysis of an indicative examples of existing Academic Analytics systems. The purpose of this analysis is to identify the level of accommodation that these systems' functionalities provide in terms of each Academic Analytics objective and identify potential shortcomings,
- providing a basis for formulating the proposed School Analytics framework (Section 4.3) by highlighting the objectives of Academic Analytics which could be useful for supporting the macro-layer K-12 school leadership tasks.

Table 12: Consolidated overview of Academic Analytics objectives and related elements

AA Objective	Common data types utilized	Main Purposes	Role involved
O1. Student Management	• **AA-O1-DT1.** Demographic da • **AA-O1-DT2.**Admission and p academic records • **AA-O1-DT3.** Course enrollme status • AA**-O1-DT4.**Grants administered	• **AA-O1-P1.** Overview of student's data • **AA-O1-P2.** Recommend best student candidates • **AA-O1-P3.** Predict admission / enrollme rates	HEI leaders HEI faculty
O2. Infrastructu management	• **AA-O2-DT1.** Quantity and quality of physical and digital resources • **AA-O2-DT2.** Level of usage o resources	• **AA-O2-P1.** Overview of HEI infrastructur • **AA-O2-P2.** Recommend resource procurement / maintenance • **AA-O2-P3.** Recommend resource allocati in terms of admissions / enrollments	
O3. Faculty management	• **AA-O3-DT1.** Faculty demographic data • **AA-O3-DT2.** Quality and quantity of research conduct • **AA-O3-DT3.** Student academ performance and course enrollment	• **AA-O3-P1.** Overview of faculty data • **AA-O3-P2.** Highlight underperforming faculty in terms of HEI standards • **AA-O3-P3.** Highlight curriculum / course shortcomings	
O4. Financial management	• **AA-O4-DT1.** Student tuition f and grants • **AA-O4-DT2.** Faculty related costs • **AA-O4-DT3.** Infrastructure maintenance and procureme costs • **AA-O4-DT4.** Alumni or spons fundraising	• **AA-O4-P1.** Alert provision when the financial plan of the organization sidetrac • **AA-O4-P2.** Financial resource allocation based on admission / enrollment predict • **AA-O4-P3.** Identification of external sponsors	
O5. Student retention	• **AA-O5-DT1.** Student demographics • **AA-O5-DT2.** Student financia data • **AA-O5-DT3.** Student assessment results	• **AA-O5-P1**. Generate "early warning alert to underperforming students • **AA-O5-P2.** Correlate individual students' performance to peers' • **AA-O5-P3.** Recommend educational pathways	HEI leaders HEI faculty HEI student

	• **AA-O5-DT4.** Student level of engagement in learning activities • **AA-O5-DT5.** Student prior academic performance	• **AA-O5-P4.** Facilitate the process of curriculum re-structuring	

4.2.1.3 Academic Analytics tools

Table 13 presents the analysis of an indicative sample of 7 AA systems and/or initiatives, in terms of the level of accommodation that the functionalities offered for each AA objective.

Table 13: Overview of indicative sample of Academic Analytics Systems

#	AA system	AA objective addressed	AA data type harvested		AA purpose targete
1	Course Signals* (Arnold, 2010)	O1. Student Management	• AA-O1-DT1 • AA-O1-DT2	• AA-O1-DT3	• AA-O1-P1
		O3. Faculty management	• AA-O3-DT2		-
		O5. Student retention	• AA-O5-DT1 • AA-O5-DT3	• AA-O5-DT4 • AA-O5-DT5	• AA-O5-P1 • AA-O5-P2 • AA-O5-P4
2	Bowie State University (Forsythe et al., 2012)	O1. Student Management	• AA-O1-DT1 • AA-O1-DT2	• AA-O1-DT3 • AA-O1-DT4	• AA-O1-P1
		O3. Faculty management	• AA-O3-DT2		• AA-O3-P1 • AA-O3-P2
		O4. Financial management	• AA-O4-DT1		• AA-O4-P1 • AA-O4-P2
		O5. Student retention	• AA-O5-DT1 • AA-O5-DT2 • AA-O5-DT3	• AA-O5-DT4 • AA-O5-DT5	• AA-O5-P1 • AA-O5-P2 • AA-O5-P3 • AA-O5-P4
3	University of Maryland Easter Shore (Forsythe al., 2012)	O1. Student Management	• AA-O1-DT1 • AA-O1-DT2	• AA-O1-DT3 • AA-O1-DT4	• AA-O1-P1 • AA-O1-P3
		O3. Faculty management	• AA-O3-DT2		• AA-O3-P1
		O4. Financial management	• AA-O4-DT1		• AA-O4-P1 • AA-O4-P2

		O5. Student retention	• AA-O5-DT1 • AA-O5-DT2	• AA-O5-DT3 • AA-O5-DT5	• AA-O5-P1 • AA-O5-P2
4	RIO PACE (Smith al., 2012)	O1. Student Management	• AA-O1-DT1 • AA-O1-DT2 • AA-O1-DT3		• AA-O1-P1
		O5. Student retention	• AA-O5-DT1 • AA-O5-DT3	• AA-O5-DT4 • AA-O5-DT5	• AA-O5-P1 • AA-O5-P2
5	University of Phoenix (Pirani & Albrecht, 2005)	O1. Student Management	• AA-O1-DT1 • AA-O1-DT2	• AA-O1-DT3 • AA-O1-DT4	• AA-O1-P1 • AA-O1-P3
		O2. Infrastructure management	• AA-O2-DT1		• AA-O2-P1 • AA-O2-P2
		O3. Faculty management	• AA-O3-DT2		• AA-O3-P1 • AA-O3-P2
		O4. Financial management	• AA-O4-DT1 • AA-O4-DT2	• AA-O4-DT3 • AA-O4-DT4	• AA-O4-P1 • AA-O4-P2
		O5. Student retention	• AA-O5-DT1 • AA-O5-DT3	• AA-O5-DT4 • AA-O5-DT5	• AA-O5-P1 • AA-O5-P2 • AA-O5-P3 • AA-O5-P4
6	MAP-works (Woosley & Jone 2011)	O1. Student Management	• AA-O1-DT1 • AA-O1-DT2	• AA-O1-DT3	• AA-O1-P1
		O3. Faculty management	• AA-O3-DT2		• AA-O3-P1
		O4. Financial management	• AA-O4-DT1		-
		O5. Student retention	• AA-O5-DT1 • AA-O5-DT2 • AA-O5-DT3	• AA-O5-DT4 • AA-O5-DT5	• AA-O5-P1 • AA-O5-P2 • AA-O5-P4
7	Library Cube (Co Jantti, 2012)	O1. Student Management	• AA-O1-DT1		• AA-O1-P1
		O2. Infrastructure management	• AA-O2-DT1 • AA-O2-DT2		• AA-O2-P1 • AA-O2-P2
		O5. Student retention	• AA-O5-DT1 • AA-O5-DT3		• AA-O5-P4

* *Course Signals was initially deployed as an AA tool, however it has been further developed to include LA aspect well (Gašević et al., 2015). In this table, only the AA deployment is considered*

As Table 13 depicts, the indicative sample of Academic Analytics systems/initiatives robustly supports only a fraction of Academic Analytics objectives, i.e., the HEI leadership tasks related to student management and retention. The tasks related to faculty management and financial orchestration have received less attention, but are nonetheless significantly supported.

Two identified shortcomings include:

- the limited level of accommodation for the tasks related to the orchestration of the HEI infrastructure. This is deemed significant since this macro-layer aspect can have a significant impact of the overall organizational performance (Pelgrum, 2008).
- the limited level of holistic approaches for exploiting the macro-layer data in combination, i.e., moving beyond harvesting and exploiting each data type in isolation (or with a restricted set of other data) towards facilitating systemic leadership decision support.

4.2.2 Learning Analytics

4.2.2.1 Learning Analytics: Definition

Learning Analytics refer to the "measurement, collection, analysis and reporting of data about learners and their contexts of learning, for purposes of understanding and optimizing learning as well as the environment in which it occurs" (Long & Siemens, 2011). As the above definition suggests, LA have a different core focal point compared to Academic Analytics, namely they are targeted at the micro-layer and meso layer of an educational institution (Long & Siemens, 2011; Daniel, 2015). Therefore, LA takes a standpoint primarily aimed at exploiting student-generated data towards monitoring and scaffolding students' progress, as well as improving the overall teaching practice (Chatti et al., 2012; Duval & Verbert, 2012; Diaz & Brown, 2012; Clow, 2013a; Ifenthaler, 2015; Gibson & de Freitas, 2016). Moreover, unlike Academic Analytics, the contribution of LA on a macro-layer is limited.

Learning Analytics does not take a specific educational level standpoint, i.e., it is applied to educational institutions at various level, such as K-12 schools or HEIs (Davenport et al., 2010; Elias, 2011; van Barneveld et al., 2012; Johnson et al., 2014), as well as, in the context of Massive

Open Online Courses (MOOCs) towards addressing their "massive" nature and the resulting barriers in terms of learning process orchestration (Clow, 2013b; Coffrin et al., 2014).

4.2.2.2 Learning Analytics: Methods and objectives

As aforementioned, Learning Analytics are focused at monitoring and improving the micro/meso-layer processes of the educational institutions. In order to address this goal, a significant range of analytical methods has been employed, since the spectrum of educational data that can be extracted and processed is very wide (Ifenthaler & Widanapathirana, 2014). More specifically, the main analytical methods include data mining, statistical methods (e.g., regression and correlation analysis), classification rules, clustering, social network analysis and visualization methods (Chatti et al., 2012; Clow, 2013a; Papamitsiou & Economides, 2014).

Each of the above methods is utilized towards addressing specific Learning Analytics objectives. Despite the fact that these objectives can vary, depending on the needs of the relevant stakeholders and context of application, a set of common LA objectives consists of (Verbert et al., 2012a; Chatti et al., 2014; Almosallam & Ouertani, 2014):

- **LA-O1. Student modelling**, in terms of identifying ***patterns*** within the student data**.** This objective is considered vital for effective decision support at the micro-layer. This objective is important both independently (e.g., for student data management) as well as a baseline for achieving the rest of the Learning Analytics objectives (Siemens & Baker, 2012; Clow, 2013a; Dawson & Siemens, 2014; Baker & Inventado, 2014; Peña-Ayala, 2014).
  Common data types utilized are:
  - students' personal inherent traits, e.g., demographics and learning style (Chrysafiadi & Virvou, 2013)
  - students' competence traits, e.g., level of knowledge and skills (Peña-Ayala, 2014)
  - students' motivation traits (Chrysafiadi & Virvou, 2013)
  - students' behavioral and emotional patterns (Moridis & Economides, 2009; Verbert et al., 2012a; Pardos et al., 2013)
  - a combination of the above (Lykourentzou et al., 2009; Giesbers et al., 2013)

  Given the extensive range of data types that have been reported as potentially useful for addressing this Learning Analytics objective, the set of analysis methods that has been deployed to exploit them is also significant. More specifically, common methods include social network analysis (Buckingham Shum & Ferguson, 2012), predictive modeling

(Clow, 2013a), as well as visualization tools for meaningfully depicting the above data and facilitating decision making (Ali et al., 2012; Gašević et al., 2015).

Main Purpose. The key purposes of this LA objective includes the capacity to create student profiles in order to perform analyses and identify underlying patterns that can support teachers' understanding of student performance (Dyckhoff et al., 2013). Additionally, profiling students can assist in an overarching manner in order to feed the rest of Learning Analytics objectives e.g., personalized educational resource recommendations based on students' learning styles (Drachsler et al., 2015).

- **LA-O2. Recommendation of educational resources and/or actions**. This objective aims to identify and recommend appropriate educational resources and/or actions (e.g., sequence of learning activities to follow) to both students and teachers (Bienkowski et al., 2012; Siemens, 2013; Chatti et al., 2014; Papamitsiou & Economides, 2014).
  Common data types utilized:
  Regarding students, LA approaches can utilize:
  - students' models, mentioned in LA-O1 (Drachsler et al., 2015)
  - students' quantity and type of interaction with educational resources (Dyckhoff et al., 2012; Dracshler et al., 2015)
  - assessment results (Smith et al., 2012; Huang & Fang, 2013).

  Regarding teachers, LA approaches can utilize:
  - teachers' demographics (Bozo et al., 2010; Verbert et al., 2012b),
  - teachers' competence profile (Sergis et al., 2014c **[P10]**),
  - teachers' social connections to peers (in digital repositories) (Fazeli et al., 2014),
  - teachers' level and type of interaction with educational resources (in digital repositories) (Zapata et al., 2013; Sergis & Sampson, 2016b).

  Towards harvesting and exploiting these data types, diverse analysis methods have been employed, usually in combination with each other, including user and task classification, user clustering, user modeling and profiling and rule-based recommendations (Drachsler et al., 2015).

  Main Purpose. Regarding students, this Learning Analytics objective commonly focuses on:

- identifying appropriate educational resources to support and scaffold learning in a personalized manner, e.g., by adhering to the learning style of the student (Manouselis et al., 2011; Verbert et al., 2012a) and
- identifying specific competence gaps through personalized recommendation of assessment resources (Barla et al., 2010; Drachsler et al., 2015).
- recommending educational pathways based on their prior performance and course selections (Bienkowski et al., 2012; Almosallam & Ouertani, 2014).

Regarding teachers:

- recommendation of educational resources for educational scenario design and delivery (Manouselis et al., 2013; Sergis et al., 2014c **[P10]**; Sergis et al., 2014d **[P9]**; Sergis & Sampson, 2014b **[P11]**) and
- recommendation of peers in communities of practice in order to promote professional development (Rafaeli et al., 2004).

- **LA-O3. Student assessment and performance feedback provision**. This objective relates to (a) the facilitation of the student in gaining a high level of self-awareness on their performance and progress and (b) the facilitation of the teacher to deploy effective assessment activities and feedback on demand (Tempelaar et al., 2013; Papamitsiou & Economides, 2014; Macfadyen et al., 2014). Even though this task can be incorporated in the LA-01 task, we present it as a separate task in order to outline the explicit focus on assessment and feedback provision that such approaches aim to take.

  Common data types utilized are:

  - students' level of engagement and performance in the learning process (Arnold & Pistilli, 2012; Giesbers et al., 2013),
  - students' quantity and type of interaction with educational resources (Ali et al., 2012; Dietz-Uhler & Hurn, 2013),
  - behavioral and emotional patterns (Verbert et al., 2012a; Pardos et al., 2013)
  - students' assessment results (Bienkowski et al., 2012)
  - analysis of students' social contributions and collaborations (Dawson et al., 2010; Buckingham Shum & Ferguson, 2012; Fessakis et al., 2013; Baker & Siemens, 2015), as well as
  - a combination of the above (Dimopoulos et al., 2013).

The analysis methods employed for this objective are very similar to those exploited for the LA-O1 objective, i.e., student assessment and feedback provision is strongly based on student profiles.

Main Purpose. Providing timely and detailed feedback and facilitating assessment activities is considered a significant factor for enhanced personalized learning experiences (Papamitsiou & Economides, 2014). More specifically, it can aid in the:

- assessment of students based on a variant set of performance criteria (Tempelaar et al., 2013),
- monitoring of students' competence development in relation to the curriculum objectives (Larusson & White, 2012; Howlin & Lynch, 2014).

These insights can offer a significant benefit that Learning Analytics can deliver in terms of assessing and providing feedback to students is their capacity to be deployed in large scale, by automating (partly or fully) the related tasks (Buckingham Shum, 2012). The latter is becoming increasingly important considering the rise of Massive Open Online Courses and the resulting need for providing efficient assessment methods for massively evaluating student performance and engagement (Kizilcec et al., 2013; Clow, 2013b; Gašević et al., 2014).

- **LA-O4. Prediction of students' future activity**, e.g., in terms of performance and engagement (Gašević et al., 2016). This objective primarily relates to the provision of insights to teachers (or students) on which students may be facing problems during the learning process. Therefore, such feedback can allow teachers to adapt the delivery of their teaching in order to offer targeted personalized support to individual students. Furthermore, if provided to students, this type of feedback can support self-awareness and self-improvement.

  Common data types utilized are:
  - students' level of engagement and/or performance in learning activities (e.g., Ali et al., 2012; Joksimović et al., 2015; Xing et al., 2015; Tempelaar et al., 2015)
  - analysis of students' social contributions and collaborations (e.g., Dawson et al., 2010; Agudo-Peregrina et al., 2014; Zacharis, 2015; Joksimović et al., 2015; Xing et al., 2015),
  - students' quantity and type of interaction with educational resources (e.g., Agudo-Peregrina et al., 2014; Xing et al., 2015; Junco & Clem, 2015)

- results from different types of formative and summative assessment activities (e.g., Chatti et al., 2012; Almosallam & Ouertani, 2014; Zacharis, 2015; Tempelaar et al., 2015; You, 2016)
- Students’ level and type of interaction and communication with the teacher (e.g., Dawson et al., 2010; Agudo-Peregrina et al., 2014)

Harvesting these data types requires analysis methods including social network analysis, e.g., for overseeing the students' level of participation and engagement (Dawson et al., 2010; Buckingham Shum & Ferguson, 2012), clustering methods, e.g., for formulating groups of students based on their level of academic performance and participation as well as visualization methods for making sense of the data types and highlighting important issues (Verbert et al., 2013).

Main Purpose. The analysis of the above data can lead to insights to:

- facilitate teachers to identify students at-risk early-on and, therefore, be able to provide more personalized tutoring / scaffolds to sstudents towards enhanced academic performance, motivation and engagement (Greller & Drachsler, 2012; Ali et al., 2012; Greller & Drachsler, 2012; Arnold & Pistilli, 2012; Clow, 2013a; Chatti et al., 2014),
- Support students’ self-awareness and trigger self-improvement (Verbert et al., 2012a; Verbert et al., 2013; Clow et al., 2013a),

A core benefit of such ‘predictive’ Learning Analytics is to facilitate leaders and teachers to increase the level of students' retention and performance through early warning alerts (Dyckhoff et al., 2012; Romero-Zaldivar et al., 2012; Almosallam & Ouertani, 2014; de Freitas et al., 2014; Gašević et al., 2015; Baker & Siemens, 2015). The latter, apart from the evident benefit of improving the students' outcomes, has also great potential for facilitating the leadership to meet internal and external accountability mandates related to student success (Dietz-Uhler & Hurn, 2013; Macfadyen et al., 2014).

Table 14 provides a consolidated overview of the above analysis of LA objectives, towards:

- supporting section 4.2.2.3, which presents an analysis of an indicative examples of existing Learning Analytics systems. The purpose of this analysis is to identify the level of accommodation that these systems' functionalities provide in terms of each Learning Analytics objective and identify potential shortcomings,
- providing a basis for formulating the proposed School Analytics framework (Section 4.3) by highlighting the objectives of Learning Analytics which could be useful for supporting the micro/meso-layer K-12 school leadership tasks.

Table 14: Overview of Learning Analytics objectives and related elements.

LA Objective	**Common data types utilized**	**Main Purposes**	**Role** involved
O1. Student modeling	• **LA-O1-DT1.** Students' demographics / inherent traits • **LA-O1-DT2.** Students' competence traits • **LA-O1-DT3.** Students' motivation traits • **LA-O1-DT4.** Students' behavioral / emotional patterns	• **LA -O1-P1.** Student grouping based on customizable criteria	Leader Teacher Student
O2. Educational resources recommendation	• **LA–O2-DT1.** Students' demographics / inherent traits • **LA–O2-DT2.** Students' competence traits • **LA–O2-DT3.** Students' motivation traits • **LA–O2-DT4.** Students' behavioral / emotional patterns • **LA–O2-DT5.** Students' quantity and type of interaction with educational resources • **LA–O2-DT6.** Students' assessment results	• **LA-O2-P1.** Recommend personalized scaffolding educational resources • **LA-O2-P2.** Recommend personalized assessment educational resources • **LA-O2-P3.** Recommend personalized educational pathways	Student
	• **LA–O2-DT7.** Teachers' demographics • **LA–O2-DT8.** Teachers' competence profile • **LA–O2-DT9.** Teachers' social connection with peers. • **LA–O2-DT10.** Teachers quantity and type of interaction with educational resources	• **LA-O2-P4.** Recommend personalized educational resources for educationa scenario design and delivery • **LA-O2-P5.** Recommend peers for community of practice formulation	Teacher
O3. Student assessment and performance feedback provision	• **LA-O3-DT1.** Students' level of engagement performance in learning activities • **LA–O3-DT2.** Students' quantity and type of interaction with educational resources • **LA-O3-DT3.** Students' behavioral / emotional patterns • **LA–O3-DT4.** Students' assessment results • **LA–O3-DT5.** Analysis of students' social contributions and collaborations	• **LA–O3-P1.** Assess students based on variant set of performance criteria • **LA–O3-P2.** Monitor students' competence development	Teacher Student
O4. Prediction of students' future activity	• **LA-O4-DT1.** Students' level of engagement performance in learning activities • **LA–O4-DT2.** Analysis of students' social contributions and collaborations	• **LA–O4-P1.** Prediction of students' activity trends for personalized supp by the teacher	Teacher

	• **LA–O4-DT3.** Students' quantity and type of interaction with educational resources • **LA–O4-DT4.** Student assessment results • **LA–O4-DT5.** Teachers' quantity and type of interaction and communication with students	• **LA–O4-P2.** Prediction of students' activity trends for self-regulation	

4.2.2.3 Learning Analytics tools

Table 15 presents the analysis of an indicative sample of nine existing Learning Analytics systems, in terms of the level of accommodation that these systems' functionalities offer for each Learning Analytics objective's purposes. These Learning Analytics systems were selected due to the fact that they have been reported as significant milestones in the Learning Analytics research agenda (Dyckhoff et al., 2013).

Table 15: Overview of Indicative Sample of Learning Analytics Systems

#	LA system	LA objective addressed	LA data type harvested	LA purpose targete
1	LAE-R (Petropoulo et al., 2014)	O1. Student modeling	• LA-O1-DT1 • LA-O1-DT2	• LA -O1-P1
		O3. Student assessment and performance feedback provision	• LA-O3-DT1 • LA–O3-DT2 • LA-O3-DT3 • LA–O3-DT4 • LA–O3-DT5	• LA–O3-P1 • LA–O3-P2
2	LOCO-Analyst (Ali al., 2012)	O1. Student modeling	• LA-O1-DT1 • LA-O1-DT2 • LA-O1-DT4	• LA -O1-P1
		O3. Student assessment and performance feedback provision	• LA-0O3-DT1 • LA–O3-DT2 • LA-O3-DT3 • LA–O3-DT4 • LA–O3-DT5	• LA–O3-P1 • LA–O3-P2
		O4. Prediction of students' future activity	• LA-O4-DT1 • LA–O4-DT2 • LA–O4-DT3 • LA–O4-DT4	• LA-O4-P1
3	SNAPP (Dawson et 2010)	O1. Student modeling	• LA-O1-DT4	• LA -O1-P1
		O3. Student assessment and performance feedback provision	• LA-O3-DT1 • LA-O3-DT3 • LA–O3-DT5	• LA–O3-P1

		O4. Prediction of students' future activity	• LA-O4-DT1 • LA–O4-DT5 • LA–O4-DT2	• LA-O4-P1
4	eLAT (Dyckhoff, et 2012)	O1. Student modeling	• LA-O1-DT1 • LA-O1-DT3 • LA-O1-DT2 • LA-O1-DT4	• LA -O1-P1
		O3. Student assessment and performance feedback provision	• LA-O3-DT1 • LA-O3-DT3 • LA-O3-DT2 • LA–O3-DT4	• LA–O3-P1 • LA–O3-P2
5	RealizeIT (Howlin Lynch, 2014)	O1. Student modeling	• LA-O1-DT1 • LA-O1-DT4 • LA-O1-DT2	• LA -O1-P1
		O2. Educational resources recommendation	• LA–O2-DT1 • LA–O2-DT6 • LA–O2-DT2	• LA-O2-P3
			• -	• -
		O3. Student assessment and performance feedback provision	• LA-O3-DT1 • LA–O3-DT4 • LA-O3-DT3 • LA–O3-DT5	• LA–O3-P1 • LA–O3-P2
		O4. Prediction of students' future activity	• LA-O4-DT1 • LA–O4-DT4 • LA–O4-DT2	• LA–O4-P1 • LA–O4-P2
6	MOODOG (Zhang e al., 2007)	O1. Student modeling	• LA-O1-DT1 • LA-O1-DT4	• LA -O1-P1
		O3. Student assessment and performance feedback provision	• LA-O3-DT1 • LA–O3-DT4 • LA–O3-DT2 • LA–O3-DT5 • LA-O3-DT3	• LA–O3-P1 • LA–O3-P2
7	Student Activity Monitor (Govaerts al. 2010)	O1. Student modeling	• LA-O1-DT1 • LA-O1-DT4	• LA -O1-P1
		O2. Educational resources recommendation	• LA–O2-DT4 • LA–O2-DT6 • LA–O2-DT5	• LA-O2-P1 • LA-O2-P2
			• -	• -
		O3. Student assessment and performance feedback provision	• LA-O3-DT1 • LA–O3-DT2 • LA–O3-DT4	• LA–O3-P1 • LA–O3-P2
		O4. Prediction of students' future activity	• LA-O4-DT1 • LA–O4-DT4 • LA–O4-DT2 • LA–O4-DT3	• LA–O4-P1
8		O1. Student modeling	• LA-O1-DT4	• LA -O1-P1

	StepUP (Santos et a 2013)	O3. Student assessment and performance feedback provision	• LA-O3-DT1 • LA-O3-DT3 • LA–O3-DT5	• LA–O3-P1
		O4. Prediction of students' future activity	• LA-O4-DT1 • LA–O4-DT2	• LA–O4-P2
9	Check My Activity (Fritz, 2011)	O1. Student modeling	• LA-O1-DT1 • LA-O1-DT2 • LA-O1-DT4	• LA -O1-P1
		O3. Student assessment and performance feedback provision	• LA-O3-DT1 • LA–O3-DT2 • LA-O3-DT3 • LA–O3-DT4	• LA–O3-P1 • LA–O3-P2
		O4. Prediction of students' future activity	• LA-O4-DT1 • LA–O4-DT3 • LA–O4-DT4 • LA–O4-DT5	• LA–O4-P1 • LA–O4-P2
10	Engagement Analy (Liu et al., 2015)	O4. Prediction of students' future activity	• LA-O4-DT1 • LA–O4-DT2 • LA–O4-DT4	• LA–O4-P1

As Table 4 depicts, all of the LA objectives are being accommodated by the indicative sample of LA systems. The core focus appears to be placed on the objectives "*LA-O1. Student modeling*", "*LA-O3. Student assessment and performance feedback provision*" and "*LA–O4. Prediction of students' future activity*". However, the objective "*LA-O2. Educational resources recommendation*" has also received a significant level of research attention, but it has been performed mainly in an isolated research area, namely Recommender Systems, which is increasingly being fused to Learning Analytics (Chatti et al., 2012; Verbert et al., 2012a; Greller & Drachsler, 2012).

Two significant insights can be drawn based on the above analysis:

- a limited level of accommodation was identified in terms of supporting profiling and activity logging for the *teachers*. Teachers have received much less attention towards effective profiling and activity tracking compared to students (Dyckhoff et al., 2013; Sergis et al., 2014d **[P9]**; Sergis & Sampson, 2014b **[P11]**). This general lack of efficient teacher data harvesting and exploiting (e.g., competences) is a significant shortcoming which limits the leadership capacity to have a transparent view of the micro-layer, and especially the meso-layer.

- extending the above, a limited level of accommodation for capturing data related to micro/meso layer factors, beyond the students, is observed. More specifically, the latter should include a holistic method of capturing and exploiting other micro/meso layer data (such as teaching practices utilized, physical context affordances, teacher competences etc) towards meaningfully informing the processes of educational design, delivery and reflection (Greller & Drachsler, 2012).

The analyses performed in Sections 4.2.1 and 4.2.2 on Academic Analytics and Learning Analytics respectively have resulted in a set of reflections related to their focal points and objectives. More specifically:

- **Academic Analytics** take a strong standpoint in terms of (a) organizational processes, by explicitly addressing the macro-layer of an educational institution functions and (b) educational level, by focusing on HEI. Moreover, despite their highly granulated coverage of the Business Intelligence of the educational institution, there is a lack of adequate overview of the micro-layer processes, which is viewed as a "black box" to a large degree (Macfadyen & Dawson, 2010). This fact can hinder the leadership's capacity to take institutional-wide decisions towards improving the educational outcomes of the institution, considering that there is limited consideration to the teaching practices being undertaken and how these are affected by (or affect) the processes of the meso-layer.
  In terms of applicability to the K-12 school context, Academic Analytics are not directly applicable (given their explicit HEI focus), however, their data types could provide a basis for informing relevant analytics approaches for addressing the macro-layer school leadership tasks.
- **Learning Analytics**, on the other hand, are primarily concerned with the micro- and meso- layers, towards assisting teachers and students in enhancing the effectiveness of the teaching and learning process (Arnold et al., 2014). However, existing Learning Analytics approaches cannot adequately support the macro-layer decision making processes, since they do not incorporate Business Intelligence. In terms of applicability to the K-12 school context, Learning Analytics are directly applicable (Piety et al., 2014), but, as aforementioned, have a limited institutional layer coverage. Finally, even though it is beyond the scope of this chapter, it should be mentioned that Learning Analytics need to be combined with Teaching Analytics in order to create a bridge to connect the insights of the micro layer (Learning Analytics) to the decisions made in the meso layer

(Teaching Analytics). This need has been highlighted as a core research challenge in the technology-supported Education (Wasson et al., 2016; Sergis & Sampson, 2017).

The above reflections suggest that there is no existing unifying approach towards providing support for holistic and complexity leadership in educational institutions, even more so when the context of study is narrowed down to K-12 schools. This conclusion is based on the fact that K-12 school leaders have been assigned with a complex set of tasks spanning from the highly-granulated overview of the micro-layer processes, the orchestration of the meso layer to the engagement in the operational tasks of the macro-layer (OECD, 2013c; Bush & Glover, 2014). Moreover, school leaders require *systemic* decision making support, which will not only harvest the aforementioned data, but will also analyze them in an intertwining manner towards providing feedback loops on the performance of the diverse actors of the school system and will, therefore, generate insights for school-wide action planning based on the current level of the system emergence (Coburn & Turner, 2011). However, the required *systemic* decision making support and data collection channels are not provided by either the existing AA or LA approaches, in isolation.

Under the light of the above, a need is identified for an analytics framework that will be targeted specifically at accommodating the needs of Complexity Leadership of K-12 school leaders, in terms of the required institution-wide data collection and exploitation for providing detailed feedback loops. The concept of *School Analytics* (SA) is, therefore, proposed and presented in the following section, along with the key principles of School Complexity Leadership. The focal points and objectives of School Analytics are based on (a) the core tasks of school leaders as they have been described in previous work in the form of a core School Leadership Tasks framework (SLT) (Sergis & Sampson, 2016a) and (b) the analysis of existing Academic Analytics and Learning Analytics objectives and their capacity to support the complexity K-12 school leadership by providing granulated feedback loops which can allow the leaders to influence the state of their school's emergence towards meeting their strategic plans.

4.3 School Analytics Framework for holistic data-driven School Leadership

4.3.1 School Analytics Definition

As aforementioned, school complexity leadership is a process that requires decision making at all institutional layers of the schools, based on a diverse set of data towards gaining insights on the diverse interactions of the inter-related actors of the schools. Moreover, as the analyses presented in Sections 4.2.1 and 4.2.2 highlighted, existing LA and AA approaches provide limited decision support capacity for these school leadership tasks, given their individual focal points and objectives. School Analytics (SA) aim to address this shortcoming by directly supporting the identified tasks of school leaders, as well as providing the means for cultivating and exploiting intra-layer communication and information channels of the school, necessary for nurturing both administrative as well as adaptive leadership.

Moreover, the proposed School Analytics should aim to move beyond harvesting these institutional-wide data, towards a more systemic standpoint. This should include data collection at all layers and, furthermore, identification of co-relations and interdependencies between them, again on all institutional layers, for the generation of feedback loops that could inform the strategic plans of the leadership team towards aligning the emergence state of the institution to the aforementioned strategic plans.

Overall, the SA framework is built in a bottom-up approach, sprouting from the SLT and by mapping and extending existing Analytics standpoints, utilizing the SLT as a foundational basis and benchmark. The following section presents the SA framework and highlights two core implications it can deliver to systemic school leadership.

4.3.2 School Analytics Objectives and Data Types

Table 16 presents the mapping between the SLT framework and the existing LA and AA objectives. This process aims to provide the basis of the proposed School Analytics (SA) approach, by highlighting (a) the data types and purposes to be utilized, as well as (b) the manner in which these are connected at all organizational layers.

The first implication of the proposed SA framework is directly observable from Table 16 and relates to the re-distribution of *existing* data types and purposes of LA and AA approaches, over the diverse SLT element grid. More specifically, this re-distribution highlights the need to utilize institutional data types to achieve purposes beyond their initial harvesting layer. For example, curriculum planning (currently at the meso-layer) should be informed by a highly detailed depiction of the processes occurring at the micro-layer. This depiction should span the final student learning outcomes, but also incorporate elements such as the student and teacher level of engagement, the quantity and type of interactions with educational resources, the students' parents (e.g., their level of involvement) as well as the detailed competence building progress of students. This could allow for more targeted reflections (feedback loops) for the leadership team and remedying actions to improve specific aspects of the curriculum, based on data-driven insights.

Table 16: The proposed School Analytics Framework

Institutional Layer	SLT element	LA and/or AA purposes	LA and/or AA data types	
Micro / Meso Layer	Learning Process Monitoring	-	• AA-01-DT3 • AA-02-DT2	• AA-03-DT3 • AA-05-DT4
		• LA-01-P1 • LA-02-P4 • LA-03-P1	• LA–02-DT4 / LA-03-DT3 • LA–02-DT5 • LA–02-DT8 • LA–02-DT10 • LA-03-DT1 / LA-04-DT1	• LA–03-DT2 / LA–04-DT3 • LA–03-DT5 / LA–04-DT2 • LA–04-DT5
	Learning process Evaluation	• AA-03-P2 • AA-05-P4	• AA-02-DT2 • AA-05-DT3	• AA-05-DT4
		• LA -01-P1 • LA -02-P4 • LA–03-P2	• LA-01-DT4 / LA–02-DT4 / LA-03-DT3 • LA–02-DT5 / LA–03-DT2 - LA–02-DT6 / LA–04-DT4 • LA–02-DT10 • LA-03-DT1 / LA-04-DT1	• LA–03-DT4 • LA–03-DT5 / LA–04-DT2 • LA–04-DT5
	Learner Performance Monitoring	• AA-05-P1 • AA-05-P2 • AA-05-P3	• AA-01-DT1 • AA-01-DT2 • AA-02-DT2	• AA-05-DT4 • AA-05-DT5
		• LA-01-P1 • LA-02-P1 • LA–03-P2 • LA–04-P1	• LA-01-DT4 / LA–02-DT4 / LA-03-DT3	• LA-03-DT1 / LA-04-DT1 • LA–03-DT5 / LA–04-DT2.

Institutional Layer	SLT element	LA and/or AA purposes	LA and/or AA data types	
		• LA-O2-P2 • LA-O2-P3 • LA-O4-P2	• LA–O2-DT5 / LA–O3-DT2 / LA–O4-DT3	
Micro Layer	**Learner Performance Evaluation**	• AA-O5-P2	• AA-O2-DT2 • AA-O5-DT3	• AA-O5-DT4
		• LA-O2-P2 • LA-O2-P3 • LA–O3-P1 • LA–O3-P2 • LA–O4-P1 • LA–O4-P2	• LA-O1-DT4 / LA-O3-DT3 • LA-O1-DT2 / LA–O2-DT2 • LA-O1-DT3 / LA–O2-DT3 • LA-O1-DT4 / LA–O2-DT4	• LA–O2-DT5 / LA–O3-DT2 / LA–O4-DT3 • LA–O2-DT6 / LA–O3-DT4 / LA–O4-DT4 • LA-O3-DT1 / LA-O4-DT1 • LA–O3-DT5 / LA–O4-DT2
Meso Layer	**Curriculum Planning**	• AA-O3-P2 • AA-O5-P4	• AA-O1-DT3 • AA-O3-DT3 • AA-O5-DT3 • AA-O5-DT5	
		• LA-O2-P4	• LA-O1-DT4 / LA–O2-DT4 • LA–O2-DT5 / LA–O3-DT2 / LA–O4-DT3 • LA–O2-DT6 / LA–O3-DT4 / LA–O4-DT4	• LA–O2-DT10 • LA-O3-DT1 / LA-O4-DT1
		• AA-O3-P1	• AA-O3-DT1	• AA-O4-DT2

Institutional Layer	SLT element	LA and/or AA purposes	LA and/or AA data types
	Teaching Staff Management	• AA-O4-P1	• AA-O3-DT2 • AA-O3-DT3 • AA-O5-DT3
		• LA-O2-P4 • LA-O2-P5 • LA-O3-P2	• LA-O2-DT6 / LA-O3-DT4 / LA–O4-DT4 • LA–O2-DT7 • LA–O2-DT8 • LA–O2-DT9 • LA–O2-DT10 • LA-O3-DT1 / LA-O4-DT1 • LA–O4-DT5
	Teaching staff Professional Development	• AA-O3-P1	• AA-O3-DT1 • AA-O3-DT2
		• LA-O2-P5	• LA–O2-DT7 • LA–O2-DT8 • LA–O2-DT9 • LA–O2-DT10 • LA–O4-DT5
Macro Layer	District Stakeholder Accountability	• AA-O1-P1 • AA-O2-P1 • AA-O3-P1 • AA-O3-P2 • AA-O4-P1 • AA-O4-P3 • AA-O5-P4	• AA-O1-DT1 • AA-O1-DT2 • AA-O1-DT3 • AA-O1-DT4 • AA-O2-DT1 • AA-O3-DT1 • AA-O3-DT3 • AA-O4-DT2 • AA-O4-DT3 • AA-O4-DT4 • AA-O5-DT3
		• LA–O3-P2	• LA-O1-DT2 • LA-O1-DT3 • LA-O1-DT4 / LA-O3-DT3 • LA–O2-DT8 • LA-O3-DT1 / LA-O4-DT1

Institutional Layer	SLT element	LA and/or AA purposes	LA and/or AA data types
			• LA–O2-DT6 / LA–O3-DT4 / LA–O4-DT4 • LA–O4-DT5
	Infrastructural Resource Management	• AA-O2-P1 • AA-O2-P2 • AA-O2-P3 • AA-O4-P1	• AA-O2-DT1 • AA-O2-DT2
		• LA-O2-P1 • LA-O2-P2 • LA-O2-P4	• LA–O2-DT5 / LA–O3-DT2 / LA–O4-DT3 • LA–O2-DT10
	Financial Resource Management	• AA-O4-P1 • AA-O4-P2 • AA-O4-P3	• AA-O4-DT1 • AA-O4-DT2 • AA-O4-DT3 • AA-O4-DT4 • AA-O5-DT2
	Learner Data Management	• AA-O1-P1 • AA-O1-P2 • AA-O1-P3 • AA-O2-P3 • AA-O4-P1 • AA-O4-P2	• AA-O1-DT1 / AA-O5-DT1 • AA-O1-DT2 • AA-O1-DT3 • AA-O1-DT4 / AA-O5-DT2 • AA-O3-DT3 • AA-O4-DT1 • AA-O5-DT3 • AA-O5-DT5
		• LA -O1-P1 • LA–O3-P2	• LA-O1-DT1 / LA–O2-DT1 • LA-O1-DT2 / LA–O2-DT2 • LA-O1-DT3 / LA–O2-DT3 / LA-O3-DT3 • LA-O1-DT4 / LA–O2-DT4 • LA–O2-DT6 / LA–O3-DT4 / LA–O4-DT4

The second implication of the proposed SA framework aims to propose *extensions* of the existing analytics approaches. These extensions, which are also informed by the shortcomings of existing LA and/or AA systems highlighted in Sections 4.2.1.3 and 4.2.2.3, mainly relate to advancing the SA purposes for facilitating school complexity leadership by enhancing the communication and information channels of the school, necessary for nurturing both *administrative* as well as *adaptive leadership*.

- **Transparent learning process monitoring / Learning process evaluation / Curriculum planning.** School Analytics posits the standpoint that there is need for *holistic* exploitation of institutional data towards effective monitoring and evaluation of the learning (and teaching) processes of the micro-layer, as well as the curriculum planning processes of the meso-layer.
  This standpoint, however, requires solid foundations in terms of the involved factors' data. As aforementioned, however, not all of these factors are adequately being profiled. For example, teachers have received very little research attention in terms of profiling, in contrast to students (Sergis et al., 2014d **[P9]**; Dyckhoff et al., 2013). This is a significant shortcoming, since the profile of the teacher (e.g., in terms of competences) can greatly affect the organizational development of the school especially in terms of the use of ICT in the teaching process (European Commission, 2013b). Therefore, SA opts to incorporate detailed profiling mechanisms for teachers (e.g., Bozo et al., 2010; Fazeli et al., 2014; Zapata et al., 2013), and utilize these data towards providing a more transparent view of the micro/meso-layer processes. Moreover, explicit profiling of other factors involved in the micro- and meso-layer processes is also required e.g., the specific teaching method utilized, as well as the full range of the school's physical and digital infrastructure being exploited.
  SA, therefore, argues that having these detailed data on the micro- and meso-layer processes can unlock the potential for highly granulated evaluations, by correlating the students' level of engagement and final outcomes to the factors that directly affect it (e.g., Sergis et al., 2017b). These data-driven monitoring and evaluation processes could enable targeted reflections and adaptations, both on-the-fly, as well as in a summative manner.
- **Redefine "best" teaching practice.** In addition to the above SA implication, these highly profiled and robustly evaluated teaching practices could be shared amongst web-based teaching communities, towards the formulation of "conditional best teaching practice" pools. These pools of teaching practices will be available to be selected as "best" for re-use by other interested teachers on a conditional manner, i.e., by considering not only the final student outcomes, but also the context in which these student outcomes were achieved. Therefore, each teacher will be able to receive recommendations based on the compatibility of each "best" practice in terms of their own school context, and make more informed selections.

- **Recommendations for targeted teacher professional development.** Another implication of SA building on the need for refining teacher competence profiling mechanisms, relates to the provision of recommendations for targeted professional development opportunities addressed to individual teachers (relevant to the School ICT competence management system presented in section 2.4). More specifically, teachers highlighted with a low level of certain competences should be facilitated in identifying specific professional development opportunities tackling their individual shortcomings (Sergis et al., 2014a **[P2]**).
- **Targeted recruitment of teachers.** School principal leaders could also utilize SA in order to receive recommendations on teacher candidates whose competence profile matches their school's related needs. This process could utilize the detailed profiles of the existing teachers and, therefore, the competence-related needs of the school, as well as existing frameworks for targeted teacher recruitment (e.g., Bowles et al., 2014).
- **Usage-informed infrastructural resource management.** SA argues that the capacity of school leaders to perform this task can be significantly supported beyond the existing approaches, by also considering the micro- and meso-layer data related to student and teacher exploitation of existing infrastructure. The latter can drive the leader to orchestrate more effectively both available infrastructural resource allocations as well as procurements, given that usage data will be available to highlight needs, trends, as well as the outcomes of each strategic plan.
- **Overarching financial resource management.** Finally, all the above SA implications can have a direct impact on facilitating the school leader to delineate a more focused and accurate financial plan, given that the processes of the school which directly or indirectly affect the financial plan will be more strategically organized and implemented towards "optimal" resource allocation, especially considering the increasingly reduced available financial resources.

As a result of the above, SA aims to facilitate school leaders to not only drive their school development in a more transparent data-driven manner through the continuous institution-wide feedback loops. Such data-driven school complexity leadership has the capacity to allow for driving internal school improvement strategic planning as well as for meeting emerging external accountability trends, which posit for qualitative proof of the quality of the practices undertaken within schools (Altrichter & Kemethofer, 2015).

4.4 Conclusions

This chapter introduced the concept of School Analytics as a framework which aims to support the complex tasks of K-12 school leaders, as the latter are described in the previously proposed School Leadership Task framework. The formulation of the

School Analytics framework was based on the foundations of school complexity leadership and its essential aspects of feedback loops and emergence. In this context, a critical overview of the two main existing educational analytics strands, namely Learning Analytics and Academic Analytics was performed, focused on the core focal points and objectives that each analytics strand adopts, both conceptually, as well as in terms of systems, by focusing on an indicative sample of "milestone" systems and initiatives. The aim of this overview was to identify whether these Analytics strands can adequately support crucial aspects of school complexity leadership (i.e., continuous feedback loops) in the holistic manner that is required, and to identify specific shortcomings.

The aforementioned analyses pinpointed the shortcomings of the existing analytics strands (individually) to fully accommodate the required holistic needs of K-12 school complexity leadership. More specifically, these limitations were related to (a) the isolated focal point of each analytics strand in terms of data collection and educational context of use and (b) the restrictive confinements imposed in the manner in which the collected data types were being exploited, i.e., with very limited *systemic* exploitation towards overarching organizational improvement.

Taking a step towards addressing these issues, the framework of School Analytics was introduced. School Analytics was built using a bottom-up approach using the School Leadership Task framework as a foundational basis to address the shortcomings of the existing analytics strands. The two core implications of the proposed SA framework relate to (a) meaningfully bridge the existing analytics' objectives towards informing school leadership at all institutional layers through the generation of continuous feedback loops, and (b) extend them in order to eliminate identified shortcomings and enable the provision of decision support recommendations which could facilitate school leaders to capture the current state of emergence of their school and to meaningfully align their strategic plans to it.

Overall, the proposed concept of School Analytics is proposed as a backbone framework for the design of systems which can potentially provide school leaders with the capacity to (a) robustly scan the current level of performance of their school, and (b) have access to robust evidence on the outcomes that it delivers and how can it be adjusted to drive organizational progress. Therefore, additional research is needed for designing, implementing and evaluating SA systems with the goal of supporting school leaders to navigate their institutions in a strategic, data-driven manner towards meeting the pressing mandates of both official external accountability as well as internal school self-evaluation and improvement (e.g., Sergis et al., 2017b).

Apart from a highly granulated overview of the complexity School Leadership tasks and the proposal of the School Analytics framework to model these tasks and support data-driven decision making, the previous chapters highlighted a key shortcoming of existing works related to the limited focus of existing decision support systems. More specifically, the focus of existing decision support systems for K-12 school leaders has been primarily set on the tasks related to external school accountability metrics and evaluations. Thus, the core aims of such systems were shown to be mainly addressed at providing a quantitative overview of specific organizational processes of schools, which are commonly used as a basis of external accountability. However, less attention has been placed on providing targeted recommendations to leaders (especially teachers) towards enhancing their capacity to engage in tasks related to (internally-led) sustainable school improvement. A key example of this was related to the facilitation of school teachers to engage in the tasks of (designing and) monitoring their teaching practice, by explicitly considering their competence profiles (Mandinach & Gummer, 2015). Therefore, additional research needs to be focused on proposing methods and systems to support teachers in engaging in these processes, and to extend them within the technology-supported context (e.g., technology-supported course design and delivery).

Based on the above, specific focus was placed on studying the potential of **recommender systems** to facilitate teacher leaders to engage in effective course design and delivery using ICT resources, by considering their ICT competence profiles. The following chapter discusses the state-of-the-art in the research field of recommender systems for supporting teachers' decision making and presents the contribution made in this research strand.

5 ICT competence-based Learning Object Recommendations for Teachers

5.1 Introduction

Recommender Systems (RS) are software tools designed to assist users in tackling the information overload problem by highlighting suitable items in a personalized manner (Bobadilla et al., 2013). They have been used in a wide range of application contexts, spanning from the movie industry (Bobadilla eta l., 2011) to e-commerce (Huang et al., 2007) and Technology-enhanced Learning (TeL) (Manouselis et al., 2013).

RS have been implemented based on an increasing number of techniques, the most prominent and commonly used being the content-based filtering, the collaborative filtering, the demographic filtering and the hybrid approaches (Bobadilla et al., 2013). The content-based filtering systems generate recommendations based on users' past choices and the content similarity between the items that were favoured in the past to novel ones that have not yet been discovered (Lops et al., 2011). The collaborative filtering systems utilize the users' ratings over the available items for providing recommendations based on information provided by the "like-minded" neighbours of the active user (i.e., the user currently using the system and receiving the generated recommendations) (Schafer et al., 2007). The demographic filtering relies on the assumed commonalities that users with similar demographic backgrounds will have (Burke, 2002). Finally, hybrid approaches combine techniques from the other approaches in order to reap the benefits of all, while tackling their individual drawbacks (Burke, 2007).

In order to provide their personalized services, RS are usually implemented to automatically gather data from the users towards capturing their unique attributes, creating and updating individual profiles (Marin et al., 2013). The reason for this is that users tend to either not manually provide personal data, or they do not provide them in an accurate manner, at a great cost to the RS prediction capacity in both occasions (Marin et al., 2013a). Therefore, and in-line with the general need for constructing and exploiting highly granulated user profiles in RS applications (Adomavicius & Tuzhilin, 2005), intelligent mechanisms should be employed in order to collect and process meaningful user data for inferring essential user characteristics that could provide added value in the quality of recommendations.

In the context of TeL, RS have been primarily utilized for the recommendation of different types of Learning Objects (LO) based on individual teachers' and learners' profiles. Nevertheless, although learners' profiling has been extensively considered, teachers' profiling is almost neglected (Sergis et al., 2014d **[P9]**). Taking into consideration, the important role of teachers in adopting technology-supported school-based educational innovations (Goktas et al., 2013), the complexity of technology-supported teaching practice (Solar et al., 2013) and the current diversity of individual teachers' digital competences (Sang et al., 2010), it is safe to assume that individual teachers' professional ICT competences profiling is an important element to be considered in educational RSs and, thus, it is worthy to investigate this topic.

To address this issue, this chapter proposes a LO recommendation approach that aims to support teachers in identifying and selecting educational resources for their course design and delivery, taking into consideration the individual teacher's current ICT competence status (Sergis et al., 2014c **[P10]**). The contribution of the proposed system is twofold. First, the RS dynamically elicits and updates the teachers' ICT Competence profiles, based on the teachers' continuous usage behaviour patterns within Learning Object Repositories (LORs) which they browse in search of educational resources for their courses. Second, the recommendation process itself adopts a new method for generating the LO recommendations by exploiting the previously mentioned elicited ICT Competence profiles, i.e. (a) by creating an ICT Competence-based neighbourhood and (b) by promoting the LOs that the active teacher is currently competent in using.

The proposed system is presented and evaluated following a two-layer approach, in line with the commonly accepted layered evaluation methodology (Brusilovsky et al., 2004) of adaptive learning systems, which has been extended to RS in (Manouselis et al., 2014). More specifically, a separate presentation and evaluation is performed for (a) the teacher ICT competence profiling mechanism (i,e., the "Teacher ICT Competence Profile Elicitation" Layer) and (b) the teacher ICT competence-based recommender mechanism (i.e., the "Learning Object Recommendation Generation" Layer).

The remainder of this chapter is structured as follows. Section 5.2 presents the background of the present study. Section 5.3 presents the proposed ICT Competence-based LO recommender system in terms of its two Layers, namely (a) the teacher ICT Competence Profile Elicitation Layer, which dynamically elicits teachers' ICT Competence profiles based on their usage behavior within Learning Object Repositories and (b) the ICT Competence-based Learning Object Recommendation Generation Layer, which exploits the elicited teachers' ICT competence profiles to provide more informed LO recommendations. Section 5.4 presents a detailed analysis of the evaluation methodology and the evaluation results for both Layers of the proposed RS. Finally, Section 5.5 contains the conclusions of the present work and the future work in this research agenda.

5.2 Related Work: Teacher-oriented Recommender Systems in Technology enhanced Learning

5.2.1. User profiling

User profiling is a technique that has been widely applied in a range of software applications, including Adaptive Web Systems (Brusilovsky & Millán, 2007) and

Recommender Systems (Ricci et al., 2011). It involves gathering data from the users in order to create a profile for each of them, depicting their unique attributes in the context of the system's application (Schiaffino & Amandi, 2009). The latter could involve, for example, movie genre preferences in a movie recommender system (Bobadilla et al., 2011), or learner preferences in an educational RS (Ferreira-Satler et al., 2013).

The process of creating individual user profiles in software applications is essential because each user has his/her own characteristics and needs. Therefore, capturing these user attributes is necessary for enabling the provision of personalized services (Qi, 2010). A user profile, therefore, presents the system's full interpretation of the users' preferences and personal characteristics.

In many cases, user profiles are not provided by the users themselves but they are being elicited automatically through the identification, collection and processing of relevant user actions' data (Al-Shamri & Bharadwaj, 2008). The reason for this is that users are usually either unwilling to provide such information or when they do, the validity and completeness of the provided data cannot be ensured (Belk et al., 2013). Therefore, the elicitation process is usually based on the users' *relevance feedback data* (Marin et al., 2014).

Relevance feedback data can be attained in two ways, namely explicit feedback and implicit feedback (De Gemmis et al., 2010). The former requires users to perform specific actions that will inform and update their profile attributes, e.g., assign ratings to items or download items. This approach provides a set of benefits for the hosting RS system, such as increased development simplicity and enhanced accuracy in the profile update process (Zanker & Jessenitschnig, 2009). Users' implicit feedback refers to mechanisms that monitor the users' interaction with the system in an unobtrusive manner. Such approaches have been developed in order to completely detach the user from the explicit feedback-providing process and maximize the amount of data that are being harvested by the system (Marin et al., 2013b). Examples of user actions that are being monitored for profiling purposes include browsing time in each item and type of items accessed, uploaded or ignored (Schiaffino & Amandi, 2009).

5.2.2 Teacher profiling in Recommender Systems

In the context of Technology-enhanced Learning (TeL), the majority of the implemented RS targets the learners and aims to provide them with personalized learning material and sequences of learning activities towards specific educational goal attainment (Manouselis et al., 2013). The main learner attributes that are being used in such processes include their prior knowledge, learning preferences/styles, individual goals and other cognitive characteristics (Chrysafiadi & Virvou, 2013). Subsequently, user profiling approaches have been primarily focused on accommodating the attributes of the learners (Garcia-Martinez & Hamou-Lhadj, 2013).

However, despite the fact that learners are indeed the main focus of learning processes, other actors are also important for the successful implementation of effective learning procedures. More specifically, teachers also play a vital part in the educational processes and, amongst other reasons, their ICT competences (Sang et al., 2010; Goktas et al., 2013) and personal attitudes towards ICT use (Tondeur et al., 2010) can greatly affect the level and the quality of their technology-supported teaching practice. Therefore, systematic accommodation of teachers' professional characteristics should be an important design consideration for educational RS. Within this context, Sergis et al., (2014d) (**[P9]**) performed a literature review of existing teacher-oriented educational RS. The 22 identified approaches are summarized in Table 17. Table 17 also contains information on the types of relevance feedback data that are being harvested. These relevance feed-back data include *Explicit* and *Implicit* data. The former include Social data (e.g., ratings and bookmarks) and user Demographic data, while the latter include, for example number of views of LO. Moreover, Table 17 presents information on whether these data are being utilized only for ad-hoc similarity calculations (i.e., they do not incorporate profile creation) or if they are being automatically processed and exploited to create dynamic and adaptive user profiles for providing personalized recommendations (i.e., they do incorporate profile creation).

Table 17: Existing teacher-oriented TeL Recommender Systems

	RS	Relevance Feedback Data	Profile Creation
1	Zapata et al. (2013)	Explicit: Demographic Explicit: Social Implicit	×
2	Manouselis et al. (2010)	Explicit: Social	×
3	Limongelli et al. (2012)	-	×
4	Bozo et al. (2010)	Explicit: Demographic Explicit: Social	×
5	Walker et al. (2004)	Explicit: Social	×
6	Rafaeli et al. (2004)	Explicit: Social	×
7	Shelton et al. (2010)	Implicit	✓
8	Brusilovsky et al. (2010)	Implicit Explicit: Social	✓
9	Schoefegger et al. (2010)	Explicit: Social	✓
10	Wang & Sumiya (2010)	-	×

11	Zaldivar & Burgos (2010)	-	×
12	Avancini & Straccia (2005)	Explicit: Social	×
13	El Helou et al. (201)	Explicit: Social	×
14	Tsai et al. (2006)	Explicit: Social	×
15	Sielis et al. (2012)	-	×
16	García-Valdez & Parra (2009)	Explicit: Social	×
17	Schirru et al. (2010)	Explicit: Social Implicit	✓
18	Drachsler et al. (2009)	Explicit: Social	×
19	Fazeli et al. (2014)	Explicit: Demographic Explicit: Social	✓
20	Dron et al. (2010)	Explicit: Social	×
21	Cobos et al. (2013)	Explicit: Demographic Explicit: Social	×
22	Ferreira-Satler et al. (2013)	Explicit: Social Implicit	✓

Only (completed) systems utilizing the above techniques were considered. Table values designated as "no" either a lack of user profiling mechanism in the corresponding system or lack of specific presentation of relevant data in the presenting paper. As Table 17 depicts, existing teacher-oriented RS utilize a wide range of "raw" relevance feed-back data types for creating user profiles. More specifically, most RS utilize "Explicit: Social" relevance feedback data (N=17, x=77%). "Implicit" (N=5, x=23%) and "Explicit: Demographic" (N=4, x=18%) relevance feedback data are used less often. However, regardless of the type of the relevance feedback utilized, the Table 1 data signify that only a small portion of existing teacher-oriented RS (N=6, x=27%) create, maintain and exploit user profiles for providing enhanced recommendations to teachers, based on these relevance feedback data. This can be considered as potential drawback, since systematic and efficient user modelling is an essential element of successful RSs (Adomavicius & Tuzhilin, 2005).

More specifically, Shelton et al. (2010) describe a system that utilizes the teachers' clicks and time on each webpage to detect their preferences and alter the recommendations accordingly. Brusilovsky et al. (2010) propose a social navigation approach for assisting teachers to identify useful educational resources within web-based repositories, through manipulation of their usage history and explicit feedback. Schoeffeger et al. (2010) and Schirru et al. (2010) proposed a method for identifying emergent topics that teachers are dealing with and are interested in. Fazeli et al. (2014) proposed a method for collecting both demographic and social data from teachers towards utilizing them for building trust networks. Finally, Ferreira-Satler et al. (2013) propose an ontology-based fuzzy teacher profile inference system. The main idea is to elicit the preferences of the teachers based on the semantic importance of each LO that they create or browse. This importance is derived from lexical analysis of the LOs and is calculated against the existing teacher profile.

A careful analysis of the existing approaches highlights the fact that key teachers' individual professional capacity characteristics, such as their aforementioned ICT Competences, are not being currently exploited for providing personalized recommendations to support their daily teaching practice of course design and delivery. Incorporating such information can lead to more focused recommendations by forming better teacher neighbourhoods and by filtering candidate LOs to identify the most appropriate for each individual teacher's ICT competences. Our previous work (Sergis et al., 2014c **[P10]**) has presented initial evidence that incorporating this type of teacher characteristics in the LO recommendation process depicted in a formal manner (i.e., the UNESCO ICT Competency Framework for teachers (Zervas et a., 2014)) and appropriately mapping them (e.g., Sergis et al. (2014d) **[P9]**) to the specific LO metadata schema that each dataset employs (e.g., the Open Discovery Space Repository LO Metadata Application Profile (Athanasiadis et al., 2014)) can have a significant positive impact on the predictive accuracy of the RS.

Moreover, due to the fact that (a) competences are not reified characteristics, but evolve over time, and (b) that such data are rarely (much less correctly) provided by the teachers themselves, profiling mechanisms should strive to construct, and maintain up-to-date, highly granulated ICT Competence profiles for teachers based on their relevance feedback data (Marin et al., 2014).

In the light of the above, a research challenge can be identified, namely how can a teacher ICT Competence profile (ICT-CP) be (a) dynamically elicited based on the implicit and explicit relevance feedback data of the teachers and (b) utilized for delivering more informed LO recommendations. To the best of our knowledge, such an approach has not been previously considered in the field of RS. Such a system could provide a unified solution for providing personalized LO recommendations to individual teachers, since it would both automatically create and update teacher ICT competence profiles (ICT-CP) as well as exploit them towards informed LO suggestions. The contribution of this chapter, therefore, is the presentation of a proposed solution towards tackling this identified research challenge.

5.3 ICT Competence-based Teacher Recommender system

This section presents the proposedRS for providing LO recommendations to teachers based on their elicited ICT-CP. The proposed system is schematically depicted in Figure 6.

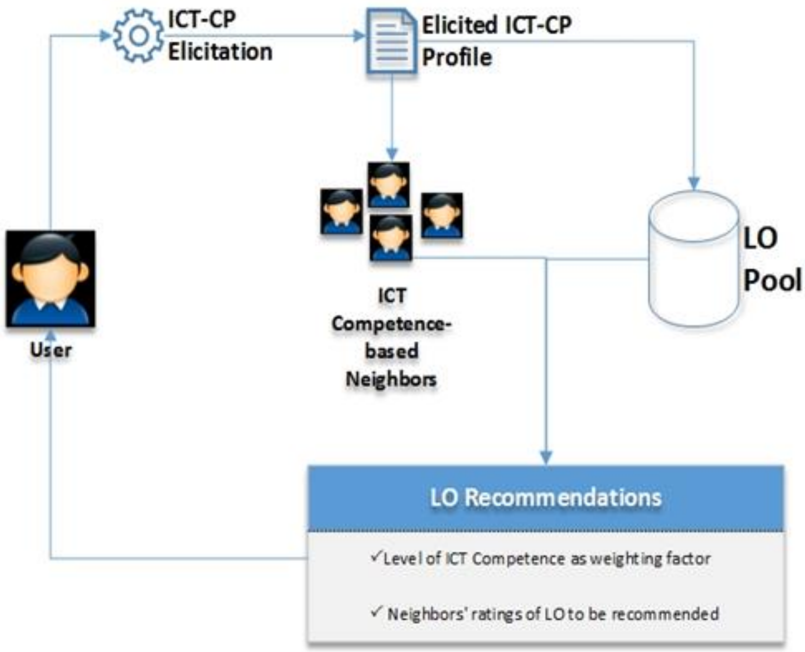

Figure 6: Overview of the proposed ICT Competence-based Teacher Recommender System

It essentially comprises two main layers, as follows:

1. **Teacher ICT Competence Profile Elicitation Layer**. The first Layer, which is described in detail in Section 5.3.1, relates to the elicitation of the active teacher's ICT-CP based on their relevance feedback data. More specifically, the system creates a unified representation of the active teacher by harvesting his/her "Usage Data" from the LOR. Following that, this unified representation is fed to the ICT-CP Elicitation mechanism and the fuzzy ICT-CP of the teachers is generated.
2. **ICT Competence-based Learning Object Recommendation Generation Layer**. The second Layer of the proposed RS is the LO recommendation generation. This is performed by utilizing the output data generated from the first Layer. More specifically, as it will be further described in Section 5.3.2, it utilizes these output data in a dual manner, i.e., (a) for the selection of the active teacher's neighbors, in terms of their ICT-CP similarity to the active teacher and (b) for weighting each candidate LO in terms of its appropriateness for the active teacher's ICT-CP. This is a promising approach, which was introduced in our previous work (Sergis et al., 2014c;2014d) and was shown to result to more accurate LO recommendations.

The presentation of the RS will be performed in two steps in accordance to the two Layers of the RS, i.e. the teacher ICT Competence Profile Elicitation Layer and the ICT Competence-based LO Recommendation Generation Layer.

5.3.1 Teachers' ICT Competence Profile Elicitation Layer

5.3.1.1 Teacher Relevance Feedback Data

The first Layer of the proposed RS relates to the elicitation of the teachers' ICT Competence profiles based on their relevance feedback data from their interaction within any LOR. Towards tackling this issue, a specific and appropriate set of relevance feedback data had to be selected. More specifically, this set should provide a valid proxy of teachers' ICT competence over the available LO type in the LOR. More specifically, the LO types referred to the distinct metadata attributes which are used to characterize LO in LORs. It should be noted that these attributes are flexible and can be adapted to meet the IEEE LOM Application Profile that each LOR adopts, in line with the official IANA MIME type extensions (http://tinyurl.com/ol2lv34).

A set of four types of relevance feedback data (from now on referred to as "Usage Data"), commonly used in the literature, was selected, as follows:

1. **Rating History**. This category included the ratings teachers had provided over the available LO. To accommodate the unique rating patterns of each teacher (e.g., some tend to rate high by default), all ratings were first normalized by subtracting the rating mean of the active teacher. Rating data could provide a solid proxy of ICT competence due to the fact that a *high* rating could imply that the user has either actually used the LO or, at least, is comfortable with it (Lops et al., 2011). A low rating on the other hand, was not be considered as an indicator of low competence, because a person would probably not rate an item low just because they would not be able to use it.
2. **Bookmarking History**. In the same vein as before, bookmarking a specific LO type repeatedly could provide insight on the fact that the active teacher utilizes this type of resources frequently in their daily teaching practice. Therefore, it could provide a solid proxy for inferring the level of relevant ICT competence of teachers.
3. **Learning Object Access History**. The access patterns of teachers could be exploited for capturing their ICT competences in the accessed LO types. More specifically, if specific LO types had been repeatedly accessed from a teacher, they could be regarded as commonly used by him/her. This could infer useful information about the teacher's ICT competence profile.
4. **Learning Object Creation History**. The last "Usage Data" category referred to active teachers' sharing history, i.e. the number of LOs that each teacher had uploaded to the LOR. These data could provide insight on the teachers' ICT Competence based on the assumption that a teacher,

who had *created* (and shared) a specific LO type, would be competent in actually using them.

These "Usage Data" types were utilized by the system for eliciting the teachers' ICT Competence profiles. More specifically, for each teacher, this process included an initial harvesting of all LOs that any of the "Usage Data" were available for. This information was then fed to the ICT Competence Profile Elicitation mechanism, towards inferring the teachers' ICT-CP.

5.3.1.2 The Teacher ICT Competence Profile Elicitation mechanism

The ICT-CP Elicitation mechanism comprised two phases, namely the "Aggregation" Phase and the "Fuzzification" Phase (Figure 7).

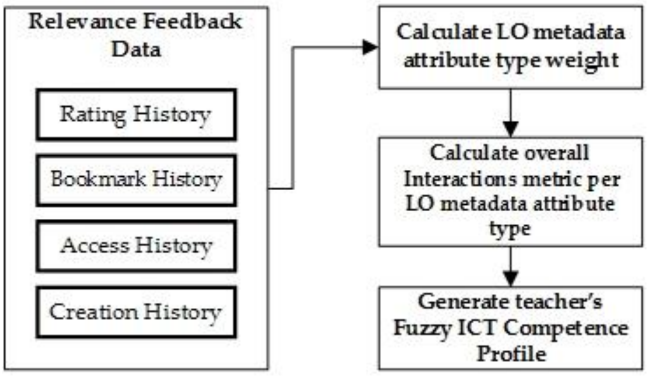

Figure 7: Overview of the proposed RS Layer 1

1. **The Aggregation Phase.** The aim of this phase is to create a unified representation of the teachers' interactions within the Learning Object Repositories (LOR). More specifically, for each teacher, all four "Usage Data" information per LO metadata attribute are merged in one "Interactions" metric. This aggregated metric provides an overview of the level of interaction that each teacher had with the diverse LO metadata types, by considering all four "Usage Data".

   In order to calculate this metric, each LO metadata attribute type received a weight representing the level of significance that it had for each teacher, i.e., the level of preference that the active teacher demonstrated to this particular LO attribute type compared to the rest within the same "Usage Data" category.

   The weights are calculated using the following formula for each teacher t:

$$w_i^t = \frac{\#LO_i}{\sum_{i=1}^{I} \#LO_i} \quad (1)$$

   where i refers to each metadata attribute type within the same "Usage Data" category and I refers to the overall cardinality of the metadata attribute set (which can vary between different LOR) within the same "Usage Data" category. The possible values for each weight range from [0 ... 1]. A weight value of "zero" for a specific LO metadata type signifies that the teacher has interacted with no

LO of this type regarding the specific "Usage Data" category (e.g, no *ratings* provided for any LO of type "video"). On the other hand, a weight value of "one" for a specific LO metadata type signifies that the teacher has interacted solely with LO of this particular type regarding a specific "Usage Data" category (e.g., the teacher has provided *bookmarks* only for LO of type "video"). Moreover, (1) also normalizes the available "Usage Data", since the different "Usage Data" categories would probably not have the same cardinality of LO (i.e., there would probably be more "Access" data than "Bookmark" data).

Therefore, building on the weights calculated in (1) for each LO metadata type, the combined "Interactions" metric is computed using the following formula, for each teacher t:

$$Interactions_j^t = \frac{\sum_{j=1}^{J} w_j^t * \#LO_j}{\sum_{j=1}^{J} w_j^t} \qquad (2)$$

where, $Interactions_j^t$ is the resulting "Interactions" metric for each LO metadata attribute type j, J is the cardinality of the “Usage Data” set and w_j^t is the weight of the j LO metadata attribute, as calculated by (1).

Therefore, for each teacher t, the "Interactions" metric presents a unified and combinative depiction of their usage pattern in a LOR, for each LO metadata attribute type by considering all four "Usage Data". This is done by considering together (a) the significance that each LO metadata attribute type had to each teacher (i.e., the weights) and (b) the number of LO per metadata attribute type that the teacher had interacted with.

2. **The Fuzzification Phase**. After the completion of the Aggregation Phase process, and the construction of the active teacher's unified "Interactions" metric, the Fuzzification Phase is activated. This step is responsible for inferring the level of the teacher's ICT competence (their ICT-CP) by translating the aggregated "Interactions" metrics for each teacher to their fuzzy equivalents. The latter would be the final proxy of the teachers' ICT Competence. The reason for employing fuzzy logic is because it is considered as an appropriate means of depicting data that are "vague" and difficult to assign to crisp categories (Hsieh et al., 2012). Therefore, apart from the extensive use of this approach for creating user profiles in different application contexts (Ferreira-Satler et al., 2013; Anand & Mampilli, 2014), fuzzy logic is selected due to the "fluid" nature of competences. More specifically, competences are not crisp characteristics, but can be attained in a continuum of proficiency levels and can be constantly updated (Sampson & Fytros, 2008).

   The adopted fuzzification process uses a set of five linguistic variables depicting levels of competence, i.e., Very Low, Low, Medium, High and Very High. The use of five linguistic variables is a typical method in the literature (e.g., Marin et al., 2013). Additionally, a triangular membership function was utilized, which is presented in Figure 8. The latter was used due to the fact that it is a commonly used membership function type for depicting characteristics similar to ours (e.g., Al-Shamri & Bharadwaj, 2008).

$$\mu_{(\alpha)} = \begin{cases} 0\,, & if\ x_i \leq x_{min}\ \boldsymbol{or}\ x_i \geq x_{max} \\ \dfrac{x_i - x_{min}}{x_{max} - \frac{x_{min}+x_{max}}{2}}, & if\ x_{min} < x_i \leq x_{min} + \dfrac{x_{min}+x_{max}}{2} \\ \dfrac{x_{max} - x_i}{x_{max} - \frac{x_{min}+x_{max}}{2}}, & if\ x_{min} + \dfrac{x_{min}+x_{max}}{2} < x_i < x_{max} \end{cases}$$

Figure 8: Membership functions of the proposed RS

where $\mu_{(\alpha)}$ represents the membership function value and it is calculated for all five linguistic variables each time, x_i represents the "Interactions" metric value and the x_{min} and x_{max} depict the minimum and maximum marginal values for each Fuzzy linguistic variable. The membership function is schematically depicted in Figure 9.

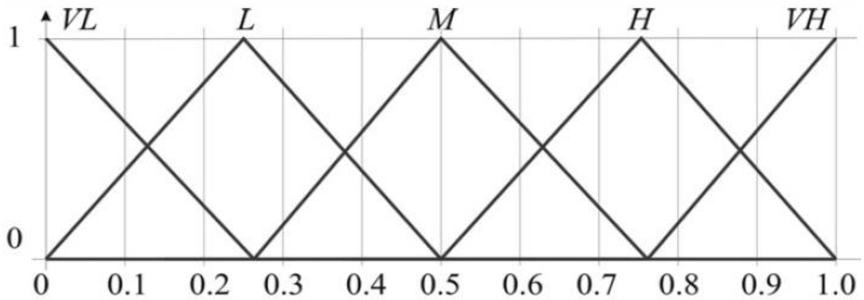

Figure 9: Schematic Representation of the Membership function of the proposed RS

To give a brief example of the above, supposing that a teacher had a resulting aggregated "Interactions" value of "0.9" (from the Aggregation Phase of the ICT Competence Elicitation mechanism) regarding a specific type of LO (e.g., "inquiry-based" Lesson Plans), their generated fuzzy ICT-CP for this LO type would be:

VL	L	M	H	VH
0	0	0	0.4	0.6

More specifically, this means that the particular teacher is 40% Highly Competent in utilizing inquiry-based lesson plans and 60% Very Highly competent. Therefore, upon completion of the process of the Fuzzification Phase, each teacher's ICT-CP has been modeled in a fuzzy manner for all LO metadata types, based on his/her "Usage Data" within the LOR. The utilization of fuzzy logic for capturing and representing teachers' ICT Competences allows for more granulated construction of profiles. In turn, this enhanced level of teacher profile granularity can assist in providing more informed recommendations (Ferreira-Satler et al., 2013). The exact manner in which this is realized in the proposed RS is described in the next section.

5.3.2 ICT Competence-based Recommendations Layer

After the completion of the processes of the first Layer, the active teacher has been assigned with a unique fuzzy ICT Competence profile depicting their personal competences in each of the distinct LO metadata attribute types stored in the LOR. At this stage, the second Layer of the RS is activated, i.e. the LO recommendation generator (Figure 10).

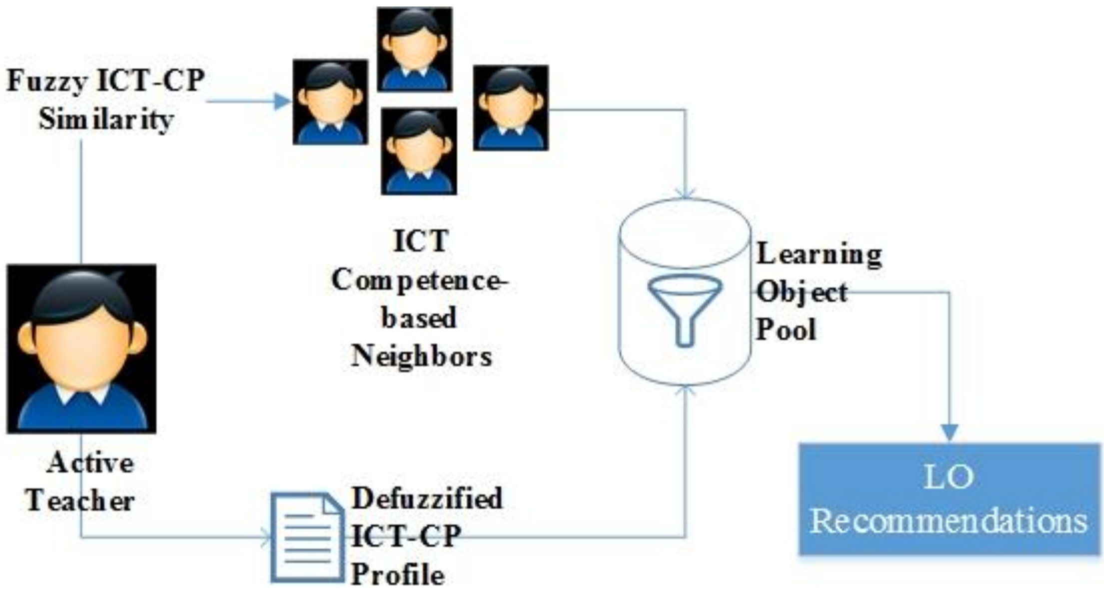

Figure 10: Overview of the proposed RS Layer 2

As aforementioned, the contribution in the proposed approach in this Layer related to the novel manner in which these recommendations were generated. More specifically, the elicited fuzzy ICT-CPs were utilized (a) as a means for neighbor selection and (b) as a weighting factor for determining the appropriateness of each candidate LO to the active teacher's level of ICT competence.

The second Layer is divided in three phases, namely: (a) the Neighbor Selection Phase, (b) the ICT Competence Defuzzification Phase and (c) the Recommendation Generation Phase.

1. **The Neighbor Selection Phase**: this phase aims at selecting the most suitable set of neighbors for the active teacher based on the similarity of their fuzzy ICT competence profiles instead of the commonly used rating similarity. In this way, the active teacher is provided with recommendations based on the opinions of colleagues that have the same ICT competence background with him/her, and thus (s)he is recommended with LO which will potentially be both useful and appropriate for them. The method employed for calculating this similarity is the Euclidean Distance, which is commonly used for similar processes (e.g., Candillier et al., 2007).
2. **The Defuzzification Phase:** this phase aims to translate the unified fuzzy teacher ICT-CP in a single factor depicting the combined level of ICT competence

of the teacher and incorporating all fuzzy levels. This factor will be utilized for weighting each candidate LO in terms of its suitability for the active teacher. The method employed for this Phase is the commonly used Center of Gravity method (Leekwijck & Kerre, 1999), which computes the center of gravity of the area under the membership function. The resulting factor of the Defuzzification Process is utilized in the second Phase of the ICT Competence-based Recommendations Layer of the RS.

3. **The Recommendation Generation Phase:** this phase aims to generate and deliver the ICT Competence-based LO recommendations. As aforementioned, the proposed recommendation method utilizes the teachers' ICT-CP profiles in a dual manner.

   First, the active teacher's neighbors are selected in Phase 1 ("Neighbor Selection Phase"), based on the similarity between their fuzzy ICT-CP. Second, the defuzzified ICT-CP factor is utilized as a filtering method of candidate LOs in terms of their appropriateness for the active teacher's level of competence.

   Based on the above, for each LO i that is being considered for recommendation, the system assesses its appropriateness score (AS) for the active teacher t using the following formula:

$$AS^t{}_i = COG_{type\ of\ (i)} * \frac{\sum_{j=1}^{N} w_j * r_{ji}}{\sum_{j=1}^{N} w_j} \quad (3)$$

   where N is the amount of neighbors that had rated the specific LO, $r_{j\,i}$ is the rating provided for LO i by neighbor teacher j and w_j is the Euclidean Distance between the active teacher and neighbor j. The Euclidean Distance is, therefore, utilized as a weighting factor in order to assign more gravity to the opinions of "closer" neighbors. Finally, the $COG_{type\ of\ (i)}$ is the output of the defuzzification process of the active teacher t. The resulting AS value represents the predicted rating for the active LO for the active teacher.

This section presented the proposed solution to the identified research challenge, i.e. a unified approach for eliciting and exploiting teacher ICT-CP towards more informed LO recommendations. The next section presents the methodology employed and results generated for evaluating the performance of the proposed system, in terms of (a) the accuracy of the ICT-CP elicitation mechanism and (b) the predictive accuracy of the RS for generating LO recommendations.

5.4 Evaluation

5.4.1 Methodology

The evaluation methodology adopted follows the layered evaluation approach (Brusilovsky et al., 2004). More specifically, monolithic evaluation of RS has been known to lead to limited remedying potential in case of low RS accuracy. Essentially, this means that a potentially low accuracy of the RS cannot be linked to the specific element of the RS that is causing this level of performance. To alleviate this issue, the layered evaluation process proposes separate evaluation Phases for each of the RS Layers, namely Phase 1 refers to the evaluation of the Teacher Profiling Layer and Phase 2 refers to the evaluation of the ICT Competence-based Recommendation Layer. In this way, any underperforming Layer can be highlighted and focused remedying actions can be performed, towards increasing the accuracy of the specific Layer, and by extension, of the overall RS.

In the context of the present study, the Phase 1 evaluation focuses on the proposed system's accuracy in re-creating existing teacher ICT-CP. More specifically, the system generates a set of teacher ICT-CP based on their relevance feedback data. The generated ICT-CPs will then be contrasted against the existing ICT-CPs, which have already been provided voluntarily by the teachers themselves in the context of the ODS Project. Moreover, it should be mentioned that the existing ICT-CPs were provided by the teachers in a manual manner, using a webform and following the well-known UNESCO ICT Competency Profile for teachers (UNESCO, 2011). The metric used for implementing this benchmark was the Jaccard co-efficient (Verbert et al., 2011). The Phase 1 evaluation was performed in two different experiments in order to enhance the robustness of results.

Regarding the Phase 2 evaluation, the main focus was assessing the accuracy of the Layer 2 of the proposed approach to predict the ratings of the active teacher on LO they had not interacted with, using the process described in (3). This evaluation phase aims at providing evidence on the positive added value and the increased accuracy of the proposed RS (depicted as Fuzzy Hybrid, abbreviated as FH) compared to existing approaches. The commonly used Root Mean Squared Error (RMSE) metric was selected for measuring the predictive accuracy (Shani & Gunawardana, 2011). This metric is calculated based on the formula:

$$RMSE = \sqrt{\frac{1}{T}\sum_{u,i\in T}(\bar{r}_{ui} - r_{ui})^2} \quad (4)$$

where $\bar{r}_{ui}$ is the set of generated predicted ratings for users u on items i, r_{ui} is the set of known ratings and T is the set of users and items for which the ratings are known. It should be noted that since this metric aims to capture errors in the predictions of the RS, lesser values of RMSE designate a better predictive accuracy of the RS.

As aforementioned, our proposed FH approach was benchmarked against a set of "control" recommendation methods, which are (a) commonly used in the literature and (b) have been reported to provide high levels of accuracy. More specifically, the control set included two types of recommendation approaches, namely user-based collaborative filtering (U) and item-based collaborative filtering (I) (Verbert et al., 2011). The former computes similarities between users to find the most similar users and predicts ratings based on how the item was rated by the most like-minded users.

The latter approach shares the same idea but it is based on similarity between items rather than between users. For each of these two recommendation approaches one similarity measure was implemented, namely the Pearson correlation coefficient (PCC) for the user-based collaborative filtering (Herlocker et al., 2002) and the Adjusted Cosine correlation coefficient (CCC) for the item-based collaborative filtering (Sarwar et al., 2001). Both similarity measures have been selected due to their reported high performance in terms of predictive accuracy in the context of their specific recommendation approach (Sarwar et al., 2001; Herlocker et al., 2002).

The Pearson correlation coefficient is calculated based on the following formula:

$$PCC = \frac{\sum_{i \in I}(r_{ui} - \overline{r_u}) * (r_{wi} - \overline{r_w})}{\sqrt{\sum_{i \in I}(r_{ui} - \overline{r_u})^2 \sum_{i \in I}(r_{wi} - \overline{r_w})^2}} \quad (5)$$

where I is the set of items that both users u and w have rated, r_{ui} and r_{wi} denote the ratings of the users u and w on the item i, while $\overline{r_u}$ and $\overline{r_w}$ denote the average ratings of the two users respectively.

The Adjusted Cosine correlation coefficient is calculated based on the following formula:

$$CCC = \frac{\sum_{u \in U}(r_{ui} - \overline{r_u}) * (r_{uj} - \overline{r_u})}{\sqrt{\sum_{u \in U}(r_{ui} - \overline{r_u})^2} \sqrt{\sum_{u \in U}(r_{uj} - \overline{r_u})^2}} \quad (6)$$

where U is the set of users that have rated both items i and j, r_{ui} and r_{uj} denote the ratings of the user u on items i and j respectively while $\overline{r_u}$ denotes the average ratings of the user.

Therefore, the overall control recommendation method set consisted of two alternatives, i.e. User-based Pearson Correlation Coefficient (UPCC) and the Item-based Adjusted Cosine Correlation Coefficient (ICCC).

For all three cases (two control approaches plus the proposed approach), the predictive accuracy evaluation process was based on the standard "Leave-N-out" technique (Herlocker et al., 2004). More specifically, this method includes splitting the available dataset in two sub-sets, namely the "training" set and the "test" set. The former contained 70% of the overall data and was used for training the RS and generating the recommendations. The latter contained the remaining 30% of the overall data and was used for evaluating the system accuracy, i.e., the recommendations generated from the training set (Verbert et al., 2011). Finally, the evaluation experiment was run for an increasing number of neighborhood size (one through twenty) in order to monitor the behavior of each approach in each occasion.

5.4.2 Datasets

The present study utilized three educational datasets for supporting the two evaluation Phases, all of which were retrieved from existing Learning Object Repositories which are currently in use. More specifically, the LORs used in our experiments were the Open Discovery Space (ODS) Repository [http://portal.opendiscoveryspace.eu], the Discover the Cosmos (DtC) Repository [http://portal.discoverthecosmos.eu], and the Open Science Resources (OSR) Repository [http://www.osrportal.eu/en/repository].

The ODS dataset, an earlier version of which was used in previous work (Sergis et al., 2014c **[P10]**; Sergis et al., 2014d **[P9])** contained (a) existing, manually provided teachers' ICT Competence profiles, depicted using the UNESCO ICT Competency Framework for teachers (ICT-CFT) (Zervas et al., 2014), (b) LO metadata records characterized using a specific IEEE LO Metadata Application Profile (Athanasiadis et al., 2014) and (c) "Usage Data" of the teachers as they were defined in Section 5.3.1.1. Due to the unique availability of existing teachers' ICT-CP, the ODS dataset was utilized for the Phase 1 evaluation process, for benchmarking the proposed teacher ICT Competence elicitation method. As aforementioned, this evaluation process was performed in two experiments each utilizing a different version of the ODS dataset (namely a first, "earlier" version and a second, more recent version). In both experiments, towards the evaluation of the re-creation accuracy of the proposed method, mapping rules were utilized for connecting ICT Competences as they were described in ICT-CFT and LO metadata attributes as they were described in the IEEE LOM Application Profile of the ODS dataset (Athanasiadis et al., 2014). These mapping rules were presented and evaluated in previous work (Sergis et al., 2014d **[P9])** . The ODS dataset was not utilized in the Phase 2 evaluation process, in order to fully adhere to the layered evaluation framework adopted, namely to not only evaluate the different layers of the proposed RS individually, but also to utilize unique datasets for evaluating each layer.

The DtC dataset [http://portal.discoverthecosmos.eu] and the OSR dataset (Sampson et al., 2011) contained (a) LO metadata records and (b) "Usage Data" of teachers that had been registered to the corresponding portals. The DtC and OSR datasets did not contain existing teacher ICT Competence profiles. Therefore, they were used only in the Phase 2 evaluation process, i.e. for evaluating the predictive accuracy of the proposed ICT Competence-based RS for teachers, by exploiting teachers' ICT-CP elicited by the first Layer of the proposed RS.

An overview of all datasets is provided in Table 18. Aggregation Level (AL) 1 LOs refer to standalone Educational Resources (e.g., flash simulations, educational games, text documents), while Aggregation Level 2 LOs refer to Lesson Plans and/or Educational Scenarios (i.e., flows of learning activities supported by Educational Resources). Overall Sample Size (N) refers to the total number of LOs in each AL category. The number of unique users refers to the cardinality of the set of teachers that had contributed at least in one "Usage Data" category. The remaining four data categories, namely Rating Data, Access Data, Creation Data and Bookmark Data, refer to the number of LOs that the corresponding "Usage Data" were provided for. As aforementioned, these four "Usage Data" categories were exploited by the proposed RS for eliciting the teachers' ICT-CP.

The OSR dataset only contained usable data for Aggregation Level 1 Learning Objects. Finally, as "unique users" for the ODS dataset were only considered those who had contributed their ICT-CP, since the purpose of this dataset was to evaluate the first Layer of the proposed RS.

Table 18: Educational Datasets Overview

	ODS Dataset (first version)		ODS Dataset (second version)		DtC Dataset		OSR Dataset
	AL1	**AL2**	**AL1**	**AL2**	**AL1**	**AL2**	**AL1**
Overall Sample Size (N)	523	475	794	519	92709	629	1545
Rating Data	1375	986	240	173	835	7469	1148
Access Data	261	99	3308	392	183	708	5026
Creation Data	523	475	794	519	92709	629	1545
Bookmark Data	63	35	177	45	47	39	345
Unique Users	115		686		209	281	829

Furthermore, regarding the Phase 2 evaluation process, in order to allow for a more informed overview of the evaluation results (presented in Section 5), an analysis of specific characteristics of the datasets utilized (i.e. DtC AL1, DtC AL2 and OSR) was performed. More specifically, this analysis was performed due to the reported high dependence of all RS's performance to the dataset to which they are fed (Verbert et al. 2011; Adomavicius & Zhang, 2012) and the resulting need to robustly understand the shift in performance of the selected RS benchmark approaches between the different datasets. Based on the works of Adomavicius & Zhang (2012) and Bobadilla & Serradilla (2009), we selected a set of two dataset characteristics that have been reported to greatly influence the level of performance of RS. These are:

1. **Rating Density.** It is defined as the ratio of known ratings against the number of all possible ratings that can be provided (i.e., $|\boldsymbol{Ratings}| \,/\, |\boldsymbol{U}| \,*\, |\boldsymbol{I}|$, where U and I are the number of users and items respectively). A logarithmic transformation was performed in order to normalize its values. Rating Density has been attributed with a high *positive* correlation to collaborative filtering RS performance, i.e., denser datasets can allow for more accurate recommendations (Adomavicius & Zhang, 2012).
2. **Rating Standard Deviation.** It is defined as the standard deviation of the ratings provided by the users in the dataset. Rating Standard Deviation has been attributed with a high *negative* correlation to collaborative filtering RS

performance, i.e., lower levels of Rating Standard Deviation can lead to more accurate recommendations (Adomavicius & Zhang, 2012).

The instantiations of the abovementioned dataset characteristics for the selected datasets for the Phase 2 Evaluation are depicted in Table 19.

Table 19: Educational Dataset Characteristics

	DtC Dataset		OSR Dataset
	AL1	**AL2**	**AL1**
Rating Density	-4,365	-1,386	-3,047
Rating Standard Deviation	0,966	0,875	0,901

As Table 19 depicts, the densest dataset is the DtC AL2, followed by the OSR and the DtC AL1. Therefore, based on the conclusions of Adomavicius & Zhang (2012), we should expect that evaluation result accuracy in each of the three datasets should follow the same correspondingly descreasing order. This intuition is supported by the Rating Standard Deviation data, which (given its negative correlation to RS accuracy) also signify the same correspondingly descreasing order in terms of expected evaluation accuracy.

Table 20 presents an overview of the evaluation methodology and datasets of this study.

Table 20: Overview of Evaluation Methodology

RS Layer	**Evaluation**			
	Dataset	**Benchmark**	**Evaluation Focal Point**	**Evaluation Metric**
Layer 1	ODS (two versions)	Existing teacher ICT-CP	ICT-CP Re-creation accuracy	Jaccard Coefficient
Layer 2	DtC, OSR	UPCC	Rating Predictive Accuracy	RMSE
		ICCC		

The following section presents the results for Phase 1 and Phase 2 of the evaluation methodology described in this section.

5.4.3 Evaluation Results

5.4.3.1 Teacher ICT Competence Profile Elicitation Method Evaluation

As aforementioned, the evaluation of the Teacher ICT Competence Profile Elicitation Method (Layer 1) was performed in two separate experiments, to increase robustness of findings.

Evaluation Results from Experiment #1

The preliminary evaluation results from the first experiment (based on the first version of the ODS dataset) are depicted in Figure 11. These results provide evidence of the proposed method's efficiency to elicit the ICT-CP of teachers based on their Usage Data. More specifically, the 'ICT-CP_{system}' re-created the existing ICT-CP_{user} (namely the profile provided manually by the teachers) at a very high degree for both Learning Object Aggregation Levels. Apart from a logical error margin in our approach, the reasons for the deviations could relate (a) to the inconsistency in the manner of depiction of ICT-CP_{system} and ICT-CP_{user} (the latter were captured in a binary format while the former were initially captured using fuzzy method), (b) the possibility of incorrect data in the ICT-CP_{user} or (c) the fact that some entries of ICT-CP_{user} could have become outdated, i.e., teachers' ICT Competences could have evolved but had not been manually updated in their profile accordingly.

Furthermore, a more detailed analysis was performed in order to identify the exact level of each of the four Usage Data type categories' effect to the level of the system's accuracy. Therefore, the evaluation experiment was repeated in additive steps, where each data type category was incrementally included in the teacher ICT Competence Elicitation mechanism. The result of this process is depicted in Figure 12.

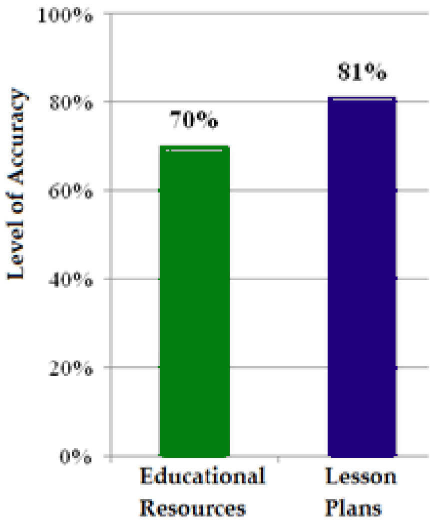

Figure 11: Overall Evaluation of the proposed teachers' ICT-CP elicitation method Accuracy

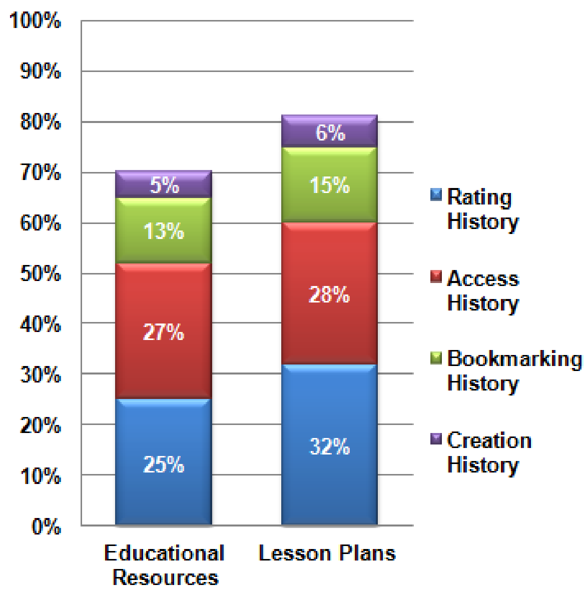

Figure 12: Detailed Evaluation of the proposed teachers' ICT-CP elicitation method Accuracy

The results of Figure 12 show that the most significant effect in eliciting the ICT Competence Profiles came from the teachers' rating and access histories. These findings can be explained based on the assumption that these data types have a more direct linkage to the teachers' actual usage patterns (and, therefore, competences), whereas bookmarking history or creation history are both more infrequently provided and have a more indirect linkage to the actual usage patterns of teachers. Moreover, regarding the creation history of the users, the low level of contribution to the overall system accuracy can be explained considering that a significant portion of teachers share pre-existing educational material that they have not created themselves, and therefore these data have a limited value for inferring the teachers' level of competence over their content. Despite this fact, however, their contribution is not negligible, and therefore, they are included in the proposed teachers' ICT-CP elicitation method.

Evaluation Results from Experiment #2

The evaluation results from the second experiment (based on the second version of the ODS dataset) are presented in Figure 13 in relation with the evaluation results generated from the experiment #1. Both sets of results provide evidence of the proposed method's high efficiency to elicit the ICT-CP of teachers based on their "Usage Data".

More specifically, for Educational Resources (AL1 LOs) the proposed system re-created the existing ICT-CP, which, as aforementioned, where provided by the teachers themselves in a manual manner through a web-form, with 70% accuracy in the initial Experiment #1 and with 73% accuracy in the updated Experiment #2. For

Lesson Plans (AL2 LOs) the ICT-CP re-creation accuracy level was 81% in the initial evaluation Experiment #1 and 79% accuracy in the new evaluation Experiment #2.

Regarding the evaluation results' accuracy levels in their own regard, they are very promising for both evaluation experiments. The reported deviations from the original, user-provided ICT-CPs can be mainly attributed to the prominent reason that teachers could have provided incorrect descriptions of their ICT competences to begin with.

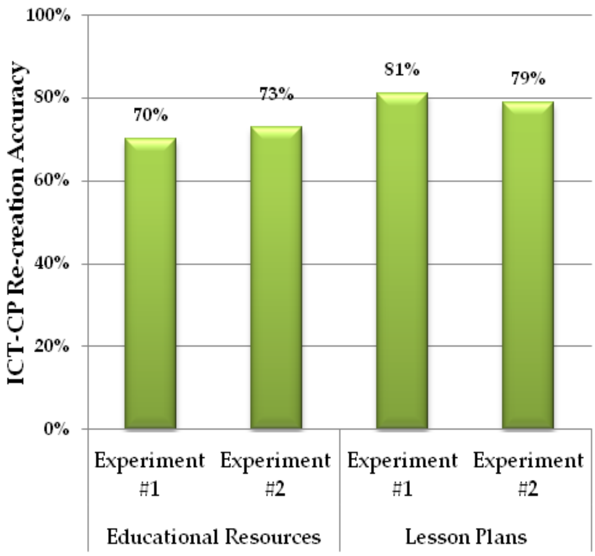

Figure 13: Results from the two evaluation experiments of the Phase 1 of the teacher ICT Competence Elicitation Mechanism

This is a very common issue in the user profiling literature, where users provide incomplete or false profiling data (Schiaffino & Amandi, 2009; Belk et al., 2013). Therefore, the manually-provided data would not always correctly represent the current level of ICT competence of the teacher that provided them, as opposed to the automatic elicitation method, which captures the teachers' *actual usage patterns* in using LOs and can therefore provide a more solid indicator of preference and competence (Marin et al., 2013b). Nonetheless, the re-creation accuracy results are significantly high in all experiments and for both Aggregation Levels despite this known shortcoming.

Moreover, regarding the result differences between Experiment #1 and Experiment #2, despite their small size, they could be attributed to the updated sets of “Usage Data" that the ODS dataset contained. These potential data alterations could have triggered these minor accuracy changes of the system, since the actual teachers' usage patterns could have been slightly altered since the initial version, without a corresponding manual change in the ICT-CP by the teacher. In any case, however, as Figure 6 depicts, the evaluation result deviations between the two Experiments are very small and the absolute evaluation results are consistent between Experiments, indicating the proposed elicitation method's robustness.

Overall, the evaluation results for the first Layer of the proposed system were promising and provided with evidence that the teacher ICT-CP Elicitation Method could be utilized within Learning Object Repositories, in order to elicit the teachers ICT-CP. As aforementioned, this information could allow for enhanced LO recommendations. The evaluation results for the latter, which represents the second Layer of the proposed system, are presented in the following section.

5.4.3.2 ICT Competence-based Learning Object Recommendations Evaluation

The second Phase in the layered evaluation of the proposed approach to LO recommendations focused on the added value it could provide in terms of predictive accuracy, by utilizing the generated teacher ICT-CP from the first Layer. As aforementioned, the DtC (for AL1 and AL2 LO) and OSR (for AL1 LO) datasets were utilized in this process. The evaluation results for each dataset will be presented in separate.

1. **Discover the Cosmos Dataset.** Figure 14 and Figure 15 depict the evaluation results of the DtC dataset for the two Aggregation Levels of Learning Objects that the dataset contained. As the Figure 14 depicts, the proposed approach outperforms both control recommendation methods for the AL1 LOs.

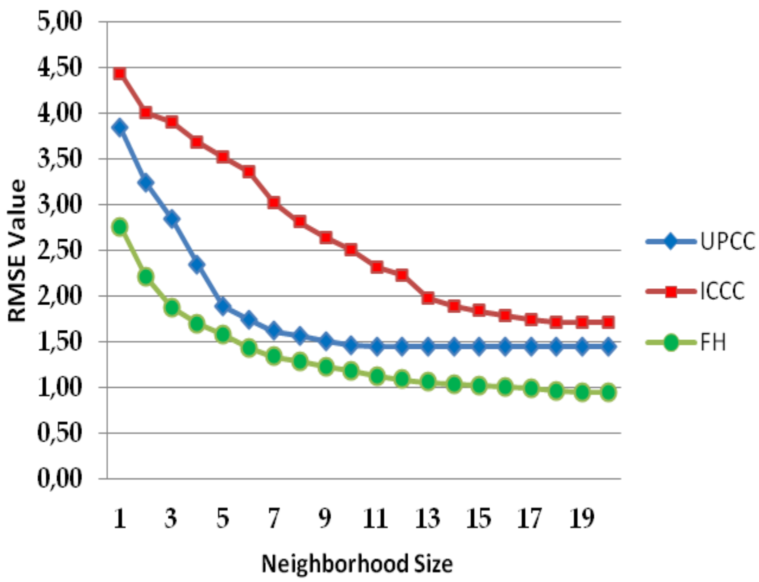

Figure 14: Predictive accuracy evaluation results for AL1 Learning Objects in the DtC dataset

Even though the accuracy of the two benchmark methods increases considerably as the neighborhood size (NS) grows, they are outperformed by the proposed FH approach for all NS values. Moreover, in the user-based control method, the threshold neighborhood size is around 10, meaning that increasing the neighbors above that threshold does not offer significant increase in accuracy.

This is because relatively few ratings and users were available in the DtC dataset for the AL1 LOs. Therefore, the user neighborhoods had limited data to be built on. This is closely related to the influence of dataset characteristics described in Section 5.4.2, and more specifically, the Rating Density (Adomavicius & Zhang, 2012). For the ICCC method this occurs at a smaller degree, since, regarding candidate neighbors at least, there is a larger pool to choose from (i.e., the AL1 LOs of the dataset). The ICCC accuracy (as well as the proposed FH's accuracy), therefore, continues to improve for a larger NS span, and begins to plateau at around 15 neighbors.

Therefore, the findings from this dataset conclude that the proposed FH approach provides more accurate LO recommendations, throughout the NS span.

Regarding AL2 LOs (Figure 15), the proposed approach similarly outperforms both control recommendation methods for all NS values. Moreover, it is important to notice that all three methods' predictive accuracy is considerably increased, compared to their AL1 equivalents.

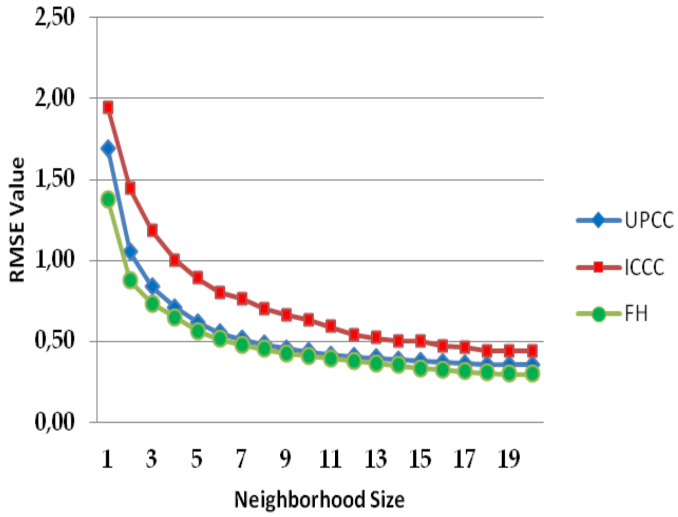

Figure 15: Predictive accuracy evaluation results for AL2 Learning Objects in the DtC dataset

The reason for this universal performance improvement can be attributed to the dataset characteristics of the DtC AL2 dataset and its comparison to its AL1 equivalent. More specifically, as Table 19 depicted, the DtC AL2 dataset was much denser (Rating Density) and had a lesser value of Rating Standard Deviation. Therefore, building on (and confirming) the findings of Adomavicius & Zhang (2012), we mainly attribute the difference of the results of Figure 14 and Figure 15 (and the enhanced predictive accuracy of the RS in the DtC AL2 dataset), to these two dataset characteristics' values.

Moreover, the significant improvement of Rating Density (compared to the DtC AL1 dataset) increased the NS threshold that provided better predictive accuracy for all three recommendation methods. More specifically, the NS threshold for the UPCC control method was increased to around 17 and for the proposed FH, as well as for the ICCC control method, the NS threshold is around 18.

Overall, despite the significant improvement in all three RS methods in the DtC AL2 datasets (compared to the DtC AL1), the proposed FH still outperformed the two benchmark methods and, essentially, delivered more accurate LO recommendations.

2. **Open Science Resources Dataset.** As aforementioned, the OSR dataset only contained usable data for AL1 LOs. The accuracy evaluation results are presented in Figure 16.

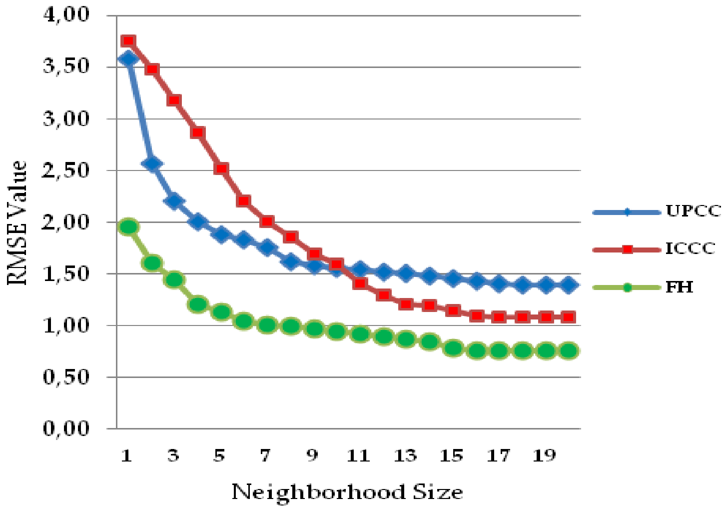

Figure 16: Predictive accuracy evaluation results for AL1 Learning Objects in the OSR dataset

As the Figure 16 depicts, the proposed approach again outperforms both benchmark methods for all neighborhood sizes. Moreover, the predictive accuracy of all approaches is decreased compared to the DtC AL2 dataset, but are better that the DtC AL1 dataset. This finding can be explained by considering the dataset characteristics presented in Table 19. More specifically, as the Table 19 data depict, the values for both OSR dataset characteristics (i.e., Rating Density and Rating Standard Deviation) are better that the DtC AL1 and worse than the DtC AL2. Therefore, the predictive accuracy results depicted in Figure 16 (and their connection to the results of Figure 14 and Figure 15) can be attributed to these facts. Regarding the NS thresholds, the results follow a similar pattern, i.e., they are increased compared to the DtC AL1 dataset and decreased compared to the DtC AL2 dataset. More specifically, the UPCC control method plateaus at around 16 neighbors, and the ICCC control method, as well as the proposed FH approach plateau at around 17 neighbors.

Therefore, the OSR dataset re-validated the promising results of the two DtC datasets, i.e. that the proposed FH approach can deliver more accurate LO recommendations to teachers, for all NS.

Overall, a consolidated overview of the predictive accuracy of the proposed FH approach provides with evidence of the added value that it can offer. More specifically, the reported promising results from Phase 2 evaluation experiments in the DtC (for both AL1 and AL2 LOs) and OSR datasets show that the proposed approach can deliver more accurate LO recommendations to teachers based on their elicited ICT Competence profiles. This is in line with the findings of our previous work (Sergis et al., 2014c **[P10]**) which presented initial evidence that incorporating (existing) teachers' ICT-CP in the LO recommendation process can provide with increased accuracy and, essentially, better results.

5.5 Discussion

This chapter aimed to address the low level of existing research work focusing on the micro- school layer, in particular for providing targeted recommendations to teachers and enhance their capacity to engage in tasks related to (internally-led) sustainable school improvement. A key example of this was related to the facilitation of school teachers to engage in the tasks of (designing and) monitoring their teaching practice, by explicitly considering their competence profiles (Mandinach & Gummer, 2015). Therefore, additional research was deemed necessary so as to propose methods and systems to support teachers in engaging in these processes, and to extend them within the technology-supported context (e.g., technology-supported course design and delivery).

Based on the above, specific focus was placed on studying the potential of recommender methods and systems to facilitate teachers to engage in more effective course design and delivery using ICT resources, by considering their ICT competence profiles. In this context, it introduced and evaluated a new RS for providing LO recommendations to teachers based on their ICT-CP elicited from their relevance feedback data. More specifically, the proposed system was divided in two Layers, namely (a) the teacher ICT Competence Profile Elicitation Layer, which was targeted at eliciting and constructing the teachers' ICT-CP based on their relevance feedback data, and (b) the ICT Competence-based LO Recommendation Layer, which utilized the elicited teacher ICT-CP from Layer 1 for providing more informed LO recommendations.

The RS evaluation followed the same layered approach and provided with evaluation results for each system Layer. Regarding the Layer 1 evaluation, two experiments were conducted and the results provided with evidence of the proposed elicitation's method capacity to elicit valid teachers' ICT-CP. Overall, both individual Layer evaluations, as well as in combination (as a holistic system), provided with evidence that the proposed approach can generate LO recommendations to teachers, which are personalized to their level of ICT competence. Moreover, the increased granularity offered by the fuzzy depiction of ICT competences was shown to have provided an added value in the overall RS performance.

Therefore, the evaluation results show that the proposed RS has the potential to be used for assisting teachers in their everyday tasks of course design, lesson planning as well as their implementation and delivery, by facilitating the process of selecting and retrieving appropriate LOs that match the teachers' ICT competence levels. Based on these insights, it is reasonable to argue that incorporating teachers' ICT competence profiles in data-driven decision support systems to support school leadership presents a promising approach. Further research should aim to expand these findings and investigate how they could scale up to support not only teachers' micro/meso layer decision making, but also holistic school strategic planning.

6 Concluding Remarks and Future Research

6.1 Conclusions

This thesis was placed within the overarching field of data-driven decision support for school leadership. In this field, the thesis critically capitalized on the existing state-of-the-art and proposed frameworks and methods to both model the complex ecosystem of schools and the tasks that school leaders perform within these ecosystems, as well as assist the decision support processes of specific aspects of school leadership, which were currently under-investigated.

More specifically, a school ICT competence profiling framework was proposed. The framework emerged from the need to pinpoint and represent the diverse dimensions affecting ICT uptake in schools, in the global context for more effective exploitation of ICT to drive systemic school improvement. Building on a critical discussion on the existing eMaturity approaches used to model ICT uptake in schools, the proposed contribution aimed to address specific oversights of these approaches and propose a more enhanced framework, by incorporating the aspect of individual and organizational competence.

The main insights and conclusions in this Research Area are as follows:

- In order to effectively capture, monitor and evaluate systemic ICT uptake in schools, it is essential to adopt a more ecosystemic conceptualization of the school environment that will host this uptake, namely the school actors and competences.
- Existing eMaturity approaches to model school ICT uptake adopted a fragmented depiction of schools and provided a limited level of modelling capacity for essential leading actors of the school ecosystem, i.e., teachers (and also principals).
- The proposed school ICT competence profiling framework provided a more detailed representation of the level of ICT uptake and use within schools and could be used by leaders (a) to have a more granulated overview of the status of their school, in order to inform their strategic planning (also potentially supported by dedicated school competence management systems) as well as (b) to promote targeted collaboration between schools, for example job shadowing and work-based professional learning projects, through selection of peer-schools with similar or complementary ICT competence profiles.
- In line with recent attempts to provide a more holistic conceptualization of ICT uptake and impact in schools and the actors that influence it (Davis et al., 2013; Vanderlinde et al., 2014; Aesaert & van Braak, 2014), it is argued that adopting a more ecosystemic conceptualization of school competences (in this case, ICT competences) is essential for understanding both the current competence status quo of each school as well as outlining targeted strategic plans for

improvement, based on specific shortcomings that can be pinpointed and traced back to their main cause(s).

Furthermore, after defining the conceptualization of schools as ecosystems, the focus shifted to investigating the globally emerging need of school leadership for data-driven decision making within such school ecosystems. Building on the complexity school leadership paradigm, a holistic School Leadership Task (SLT) framework was designed, with the aim of describing the wide range of tasks that school leaders engage with at different organizational layers of schools. Additionally, utilizing the SLT as an analysis framework, a critical review of existing commercial decision support systems aiming to facilitate school leaders was performed.

The main insights and conclusions in this Research Area are as follows:

- School leaders are faced with a diverse set of tasks, which require both appropriate competences as well as appropriate tools to be effectively conducted. Furthermore, these tasks are not always under the direct control of the school leader, but also encapsulate the actions of other actors (such as students and parents), which should be taken into account in the decisions of the leader.
- In this complex landscape, the clear majority of decision support systems that have been introduced to scaffold school leaders focus on addressing the requirements of external accountability reporting, but present fractured and limited support in terms of guiding school internal self-improvement. This reflects the global push towards robust evidence for meeting accountability mandates, but also highlights an important inconsistency, namely that in order for schools to effectively meet these accountability mandates, they first need to have established a continuous flow and culture of internal cycle of self-improvement.
- Therefore, given that internal school self-evaluation processes (especially at micro/meso layer) are a vital part of meeting external accountability mandates (as well as improving the teaching and learning conditions within the school), it is argued that additional attention should be placed on supporting K-12 leaders' data-driven decision making on the micro/meso layer so as to be able to design, orchestrate, monitor and evaluate internal strategic plans for targeted school improvement.

Building on the aforementioned insights from the critical analysis of commercial decision support systems, the *research* field of educational Analytics was studied as the means to provide a clear understanding of how it can support school leaders to meet the holistic tasks of the SLT. In this context, the insights generated argued that the existing Analytics strands (namely Learning Analytics -Teaching Analytics- and Academic Analytics) offer limited support to K12 school leaders, given the complex nature of their tasks, as depicted in the aforementioned SLT. Therefore, a more holistic School Analytics strand was proposed, which aimed to combine the focal points of the individual strands. In this way, it aimed to provide a structured framework to both describe the tasks that school leaders need to perform as well as map these tasks to the combined pool of decision support objectives of the existing individual Analytics strands. The proposed School Analytics strand could offer the backbone blueprint framework for school leaders to collect, process and visualize a more holistic set of educational data from their schools. In this way, they could more efficiently (a) identify areas in need of remedying actions within their school, as a means to trigger self-evaluation and improvement, (b) aggregate educational data as evidence of meeting the schools' external accountability mandates as well as (c) design the strategic plan of their school based on data-driven evidence and be able to track the progress of implementation against data-driven indicators.

The main insights and conclusions in this Research Area are as follows:

- Data Analytics are essential for supporting school leaders effectively capture, monitor, process and z and take decisions based on a richer pool of evidence.

Finally, placing a particular focus on teachers since they presented a largely under-investigated target group in existing works on decision support, this work aimed to alleviate this shortcoming in the context of teaching design tasks, by designing, developing and evaluating an ICT competence-based LO recommender system. The proposed recommender system extended the current state-of-the-art by providing a holistic mechanism that (a) dynamically and unobtrusively created and maintained teachers' ICT competence profiles based on their actions within LORs and (b) utilized these elicited profiles in order to recommend appropriate LOs using a novel neighbourhood and LO filtering process. The proposed RS could be embedded within existing LORs in order to enhance the level of personalization they offer to the teachers in terms of (a) community building, since teachers with similar or complementary ICT competence profiles could be matched to foster collaboration, mentoring and/or exchange of practices and (b) teaching design support, since teachers would be recommended LOs which would be appropriate for their own ICT competences and could be utilized in their teaching practice with minimal need for external technical support.

The main insights and conclusions in this Research Area are as follows:

- Teachers have received a limited level of research attention in terms of decision support methods and tools, to facilitate them engage in their daily tasks.
- Given that teachers are a vital actor of the school ecosystem and they are directly involved in any self-improvement strategies addressed at the micro-meso layers of the school, it is argued that additional research needs to be placed on designing and evaluating data-driven Analytics approaches to explicitly scaffold their capacity to engage in such strategies. This is in line with the global challenge of effectively supporting teachers' data-driven self-appraisal and self-improvement (Lockyer et al., 2013).

- Specifically considering teachers' ICT competence profiles during the personalized recommendation process led to more focused and appropriate suggestions to teachers. Even though further research should complement and corroborate these initial findings, the results support the standpoint that teachers' ICT competences can be a major factor in the adoption of ICT in school daily teaching and learning practices; and therefore decision support systems need to explicitly consider these characteristics in order to offer more meaningful support to school leadership.

6.2 Future Research

Future work in the research areas addressed in this work should capitalize on the aforementioned conclusions and further investigate the potential of (Educational) Data Analytics methods to support school leadership (especially teachers) engage in continuous school self-improvement, with a particular focus on the micro-/meso layer of the school.

In this context, a key globally identified challenge relates to supporting teachers to effectively engage in a systematic process of data-driven reflection on their teaching practice (Wasson et al., 2016), a process which is commonly termed *teacher inquiry.* Teacher inquiry is defined as a sequence of actions in which "*teachers identify questions for investigation in their practice and then design a process for collecting evidence about student learning that informs their subsequent educational designs*" (Avramides et al., 2015). Essentially, teacher inquiry is a form of action research, in which teachers define specific questions regarding their educational design and delivery and collect evidence to answer these questions (Altrichter et al., 2008). Therefore, this process can guide reflection and improvement in a systematic and evidence-based manner (Dana and Yendol-Hoppey, 2014).

Teacher inquiry generically follows a cycle of steps (Timperley et al., 2010; Hansen and Wasson, 2016), which is outlined as follows:

- *Step 1: Problem Identification*. During this step, the teacher identifies a specific aspect of their educational design and/or delivery that they wish to investigate/evaluate in order to improve it.
- *Step 2: Develop Inquiry Questions.* During this step, the teacher defines the specific questions that they will investigate, related to evaluating or investigating aspects of their educational design and/or delivery. Furthermore, the teacher defines which *educational data* they will need to collect during delivery to answer the specific question they defined, as well as the method for collecting these data.
- *Step 3: Educational Design.* During this step, the teacher formulates the educational design which they will deliver in order to implement their inquiry.
- *Step 4: Deliver Educational Design and collect data*. During this step, the teacher delivers the educational design to the learners and collects the educational data using the collection method.

- *Step 5: Analyze educational data.* After the teacher has collected the educational data, they analyse them in order to elicit insights to answer the inquiry question they have defined.
- *Step 6: Reflect on data.* Finally, the analysed data are used by the teacher in order to answer the defined inquiry question and (if needed) revise the practice in which they conduct their educational design and/or delivery.

However, the challenge in this field is that, despite the global push, specific barriers exist that hinder teachers to engage in such self-evaluation and improvement of their teaching practice. These barriers mainly include:

- teachers' low *data literacy* competences, namely competences needed to "transform data into information and ultimately into actionable knowledge" (Mandinach & Gummer, 2013),
- un-timely collection and analysis of educational data, meaning that the effort needed to collect and process educational data can introduce delays in actually using the insights, rendering them obsolete (Kaufman et al., 2014) and
- low quality of educational data that can be manually collected by the teacher, meaning that manual collection of data can be limiting in terms of the volume and type of data that can be feasibly collected as well as be prone to data contamination due to inappropriate collection or storing methods (Mandinach, 2012).
- Limited availability of resources and support for teachers to engage in reflective practice, since this is a time-consuming and cumbersome process, requiring investment of both human and technical resources (Marsh et al., 2006).

Therefore, in order to bring balance to the inconsistency between the global push and need for teacher inquiry and the significant barriers that impede the wide adoption of such practices, it is argued that educational data Analytics technologies can be utilized to remedy for the identified barriers and, essentially, enhance the data literacy capacity of teachers to engage in reflective inquiry.

In this context, a research synergy to exploit the potential of Teaching Analytics and Learning Analytics has been recently proposed, namely **Teaching and Learning Analytics** (TLA) (Sergis & Sampson, 2017). TLA is presented as a synergy between Teaching Analytics and Learning Analytics in order to holistically support the process of teacher inquiry. More specifically, TLA argues for the need for methods and tools that will exploit:

- the potential of *Teaching Analytics* to analyze the educational designs in the constituent elements (e.g., learning and assessment activities and educational resources/tools) and the interrelations between these elements
- the potential of *Learning Analytics* to measure, collect, analyse and report on learners' educational data and the learning context that they are generated,

aiming to improve the learning conditions for individual learners or groups of learners.

Overall, TLA argues that insights generated by Learning Analytics methods and tools can be mapped to the analyzed (through Teaching Analytics tools) elements of teaching design that generated them, and therefore support teachers to reflect on and improve their educational design and delivery based on evidence (Sergis & Sampson, 2017). In this regard, TLA is appropriate to support the cycle of teacher inquiry, as defined previously, as indicated in Table 2.1. Indeed, this data-driven approach to support teacher reflection is considered as one of the key research challenges in the field of Technology-enhanced Education (Wasson et al., 2016).

Table 21: Mapping between TLA and the steps of Teacher Inquiry cycle

Teacher Inquiry Cycle Steps	How TLA can contribute
1. Problem Identification	Teaching Analytics can be used to capture and analyze the educational design and facilitate the teacher to: • pinpoint the specific elements of their educational design that relate to the problem they have identified and • elaborate on their inquiry question by defining explicitly the educational design elements they will monitor and investigate in their inquiry
2. Develop Inquiry Questions	
3. Educational Design	
4. Deliver Educational Design and collect data	Learning Analytics can be used to collect the learner / teacher educational data that have been defined to answer their inquiry question.
5. Analyze data	Learning Analytics can be used to analyse and report on the collected data and facilitate sense-making
6. Reflect on data	The combined use of TLA can be used to answer the inquiry questions and support reflection on educational design and delivery

Therefore, proposed future work should be explicitly placed on investigating this emerging and promising field by extending the findings and conclusions of this work as follows:

- First, a specific research strand can be directed to design, implement and evaluate new TLA methods and tools which will allow teachers to (a) capture and analyse their existing teaching designs and (b) map these analyses to students' educational data generated from the delivery of these designs, so as to inform more targeted insights for reflection and improvement (e.g., Sergis et al., 2017a). Such descriptive and/or prescriptive TLA methods and tools could be used to allow teachers design, implement and evaluate their own inquiries, based on data collected from their unique educational context, and effectively support both their own professional development as well as the improvement of their school's capacity. Additionally, such methods could be fused with other teacher-oriented decision support systems (such as the proposed ICT competence-based recommender system), in order to deliver a more holistic environment that will not only support teachers during the design of their teaching practice, but will also facilitate them to evaluate and improve it in an evidence-based manner.

- Second, another research strand can focus on utilizing the proposed School Analytics framework as a hosting setting for new TLA methods and tools so as to allow access to a richer pool of data. More specifically, such enhanced TLA methods and tools could allow teachers to design and implement more granulated inquiries on their teaching practice, by also explicitly taking into account school-wide factors that could affect it but are potentially difficult to measure and consider, e.g., school physical and digital infrastructure or students' past records on performance and engagement.

Finally, it should be mentioned that, beyond using TLA to support teacher inquiry at the micro-/meso- layer, future work could also focus on methods and tools that will focus on holistic school improvement, capitalizing on the School Analytics framework. More specifically, extending the previous bullet-point to a more school-wide perspective (as well as the proposed school ICT Competence Management system of section 2.3), future research could also validate through user-based studies, the capacity of the proposed School Analytics framework to act as the backbone framework for decision support methods (and tools) targeted at school organizational improvement.

More specifically, beyond informing teachers' reflection on their teaching practice, School Analytics could inform new data analytics methods which would (a) exploit the multitude of educational data generated at the school in order to create a transparent school profile and highlight areas of potential improvement, (b) generate data-driven recommendations to school leaders highlighting areas of improvement as well as actions to take in order to improve them and (c) update the school profile based on the results of the remedying actions taken by the leaders (e.g., Sergis et al., 2017b). Having such transparent and granulated data pools of the way that schools operate will not only facilitate the school leaders to strategically plan for systemic improvement, but will also provide valuable aggregated insights to policymakers and researchers so as to better understand the interplay of actors within the school ecosystem and how these actors and interconnections impact student learning experiences and outcomes.

Appendix

In Table 22, the detailed list of the school leadership decision support systems identified and utilized in Chapter 3.4 is presented, i.e., their title and URL.

Table 22: List of school-oriented leadership decision support systems (SL-DSS) reviewed in Section 3

ID	SL-DSS	URL	ID	SL-DSS	URL
[1]	Fresh Grade	https://www.freshgrade.com	**[36]**	Tyler Tech	http://tinyurl.com/mnwwrqk
[2]	LongLeaf	http://www.longleafsolutions.com	**[37]**	EdPlan	http://tinyurl.com/mvk3el7
[3]	Edumate	http://www.edumate.com.au	**[38]**	IRIS	http://tinyurl.com/ljgfb9r
[4]	Jupiter Ed	http://jupitered.com	**[39]**	Learnsmart	http://tinyurl.com/nqxddsf
[5]	Ellevation	http://ellevationeducation.com	**[40]**	TalentEd	http://www.netchemia.com
[6]	Schoolzilla	https://schoolzilla.org	**[41]**	SchoolDude	www.schooldude.com
[7]	Brightbytes	http://brightbytes.net	**[42]**	Attention2Attendance	http://tinyurl.com/mzpxsfa
[8]	Learnsprout	http://www.learnsprout.com	**[43]**	Performance Matters	http://tinyurl.com/m5m4kwd
[9]	Powerschool	http://tinyurl.com/mh57pll	**[44]**	Circulus Education	http://tinyurl.com/k7g9kc2
[10]	Canvas	http://www.instructure.com	**[45]**	K12 Systems	https://www.k12system.com
[11]	Brightspace	http://www.brightspace.com	**[46]**	Schoolutions	http://tinyurl.com/kgdv8xu
[12]	SunGuard	http://sungardk12.com	**[47]**	Software Nology	http://softwarenology.com
[13]	BlackBoard Analytics	http://tinyurl.com/mglvcdt	**[48]**	K12 Enterprise	http://www.k12enterprise.com
[14]	Schoology	http://www.schoology.com	**[49]**	File Maker	http://tinyurl.com/mrynqwj
[15]	Tableau	http://tinyurl.com/pnercuj	**[50]**	eStar	https://www.esped.com
[16]	Edusight	www.edusight.co	**[51]**	Corner Stone	http://tinyurl.com/k2lmzdm
[17]	Grade Analyzer	http://www.gradealyzer.com	**[52]**	IBM Education	http://tinyurl.com/pw5vrbj
[18]	Dell ED management	http://tinyurl.com/k9bufwy	**[53]**	Mastery Connect	http://www.masteryconnect.com
[19]	Bulker Systems	http://tinyurl.com/p2ljfu6	**[54]**	Scantron Analytics	http://www.scantron.com
[20]	K12 Dynamics	http://k12dynamics.com/dashboard	**[55]**	Data House	http://tinyurl.com/mkcvo45
[21]	Its Learning	http://www.itslearning.net	**[56]**	Kinvolved	http://kinvolved.com
[22]	Skyward	http://www.skyward.com	**[57]**	Paragon K12	http://tinyurl.com/nsmclcw
[23]	Focal Point K12	http://www.focalpointk12.com	**[58]**	SAS K12	http://tinyurl.com/ne9zvwn
[24]	Dreambox	http://www.dreambox.com	**[59]**	Unissant	http://tinyurl.com/ps2mzov

[25]	Streams Junyo	http://streams.junyo.com	**[60]**	Get Alma	http://www.getalma.com
[26]	Phytorion	http://tinyurl.com/psza4p8	**[61]**	Open SIS	http://tinyurl.com/lkms2n2
[27]	P3 Strategies	http://tinyurl.com/lh2x482	**[62]**	DataBlocs K-12 Solutions	http://www.datablocs.com
[28]	Stars	http://www.schoolcity.com	**[63]**	Accelify	http://www.accelify.com
[29]	Learning Qube	http://tinyurl.com/o9jnnd7	**[64]**	KickBoard	http://tinyurl.com/6xtlxno
[30]	Class Charts	https://www.classcharts.com	**[65]**	TopScholar	http://www.topscholar.co
[31]	BlackBaud	https://www.blackbaud.com/k-12	**[66]**	MyDistrict360	http://www.mydistrict360.com
[32]	K12 Analytics	http://www.k12analytics.com	**[67]**	RealizeIt	http://realizeitlearning.com
[33]	Enlit	http://enlitllc.com	**[68]**	Teacher Match	https://www.teachermatch.org
[34]	Ed Analytics	http://edanalytics.org	**[69]**	TIES	http://ties.k12.mn.us
[35]	Illuminate Education	https://www.illuminateed.com	**[70]**	EdMin	http://edmin.com

References

ACODE (2014). *Benchmarks for Technology Enhanced Learning*. Retrieved from http://tinyurl.com/hplmg2k

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE transactions on knowledge and data engineering*, *17*(6), 734-749.

Adomavicius, G., & Zhang, J. (2012). Impact of data characteristics on recommender systems performance. *ACM Transactions on Management Information Systems*, *3*(1), 3.

Aesaert, K., & van Braak, J. (2014). Exploring factors related to primary school pupils' ICT self-efficacy: A multilevel approach. *Computers in Human Behavior, 41*, 327-341.

Agudo-Peregrina, Á. F., Iglesias-Pradas, S., Conde-González, M. Á., & Hernández-García, Á. (2014). Can we predict success from log data in VLEs? Classification of interactions for learning analytics and their relation with performance in VLE-supported F2F and online learning. *Computers in human behavior, 31*, 542-550.

AITSL (2014). Australian Professional Standard for Principals and the Leadership Profiles. [online] Retrieved from http://tinyurl.com/ow54zdm

Al-Shamri, M.Y.H., & Bharadwaj, K.K. (2008). Fuzzy-genetic approach to recommender systems based on a novel hybrid user model. *Expert systems with applications*, *35*(3), 1386-1399.

Ali, L., Hatala, M., Gašević, D., & Jovanović, J. (2012). A qualitative evaluation of evolution of a learning analytics tool. *Computers & Education, 58*(1), 470-489.

Almosallam, E. A., & Ouertani, H. C. (2014). Learning analytics: Definitions, applications and related fields. In *Proceedings of the First International Conference on Advanced Data and Information Engineering (DaEng-2013)* (pp. 721-730). Singapore: Springer.

Altrichter H, Feldman A, Posch P, Somekh, B. (2008) *Teachers Investigate Their Work: An Introduction to Action Research Across the Professions*. Routledge, London

Altrichter, H., & Kemethofer, D. (2015). Does accountability pressure through school inspections promote school improvement?. *School Effectiveness and School Improvement, 26*(1), 32-56.

Amit, R., & Schoemaker, P. J. (1993). Strategic assets and organizational rent. *Strategic management journal, 14(*1*)*, 33-46.

Anand, D., & Mampilli, B. S. (2014). Folksonomy-based fuzzy user profiling for improved recommendations. *Expert Systems with Applications*, *41*(5), 2424-2436.

Antons, C. M., & Maltz, E. N. (2006). Expanding the role of institutional research at small private universities: A case study in enrollment management using data mining. *New Directions for Institutional Research, 2006*(131), 69-81.

Arnold, K. E. (2010). Signals: Applying academic analytics. *Educause Quarterly, 33*(1). Retrieved from http://er.educause.edu/articles/2010/3/signals-applying-academic-analytics.

Arnold, K. E., Lynch, G., Huston, D., Wong, L., Jorn, L., & Olsen, C. W. (2014). Building institutional capacities and competencies for systemic learning analytics initiatives. In *Proceedings of the 4th International Conference on Learning Analytics and Knowledge* (pp. 257-260). Indianapolis: ACM.

Arnold, K.E., & Pistilli, M.D. (2012), Course signals at Purdue: using learning analytics to increase student success, In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 267–270)

Athanasiadis, N., Sotiriou, S., Zervas, P., & Sampson, D. G. (2014). The open discovery space portal: A socially-powered and open federated infrastructure. In D.G., Sampson, D., Ifenthaler, J.M. Spector, P., Isaias, P. (Eds.) *Digital Systems for Open Access to Formal and Informal Learning* (pp. 11-23). Springer International Publishing.

Augustine, C. H., Gonzalez, G., Ikemoto, G. S., Russell, J., Zellman, G. L., Constant, L., . . . Dembowsky, J. W. (2009). *Improving school leadership: The promise of cohesive leadership systems*. Santa Monica, CA: RAND Education.

Avancini, H., & Straccia, U. (2005). User recommendation for collaborative and personalised digital archives. *International Journal of Web Based Communities*, *1*(2), 163-175.

Avramides, K., Hunter, J., Oliver, M., & Luckin, R. (2015). A method for teacher inquiry in cross-curricular projects: Lessons from a case study. *British Journal of Educational Technology, 46*(2), 249-264

Axelrod, R., & Cohen, M. D. (2000). *Harnessing complexity: Organisational implications of a scientific frontier*. New York: Free Press.

Baepler, P., & Murdoch, C. J. (2010). Academic analytics and data mining in higher education. *International Journal for the Scholarship of Teaching and Learning, 4*(2), 1-9.

Bahr, P. R. (2012). Classifying community colleges based on students' patterns of use. *Research in Higher Education, 54*(4), 433-460.

Baker, R. S., & Inventado, P. S. (2014). Educational data mining and learning analytics. In J. A. Larusson & B. White (Eds.), *Learning Analytics* (pp. 79-102). New York: Springer.

Baker, R., & Siemens, G. (2015). Educational data mining and learning analytics. In K. Sawyer (Ed.), *The Cambridge handbook of the learning sciences* (2nd Ed.) (pp. 253 - 273) . Cambridge: Cambridge University Press.

Barber R., & Sharkey, M. (2012). Course correction: Using analytics to predict course success. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 259–262). New York: ACM.

Barla, M., Bieliková, M., Ezzeddinne, A. B., Kramár, T., Šimko, M., & Vozár, O. (2010). On the impact of adaptive test question selection for learning efficiency. *Computers & Education*, *55*(2), 846–857.

Barney, J. (1991). Firm resources and sustained competitive advantage, *Journal of Management, 17(*1*)*, 99–120.

BCPVPA (British Columbia Principals' & Vice-Principals' Association) (2013). *Leadership Standards for Principals and Vice-Principals in British Columbia*. [online] Retrieved from http://www.bcpvpa.bc.ca/downloads/pdf/BCPVPAStandards0913.pdf

BECTA (2002). *ICT supporting teaching: Developing effective practice* [online] Retrieved from http://homepages.shu.ac.uk/~edsjlc/ict/becta/effective_practice.pdf

Belk, M., Papatheocharous, E., Germanakos, P., & Samaras, G. (2013). Modeling users on the World Wide Web based on cognitive factors, navigation behavior and clustering techniques.*Journal of Systems and Software*, *86*(12), 2995-3012.

Bhamra, R., Dani, S., & Bhamra, T. (2011). Competence understanding and use in SMEs: a UK manufacturing perspective. *International Journal of Production Research, 49(*10*)*, 2729-2743.

bin Mat, U., Buniyamin, N., Arsad, P. M., & Kassim, R. (2013). An overview of using academic analytics to predict and improve students' achievement: A proposed proactive intelligent intervention. In *IEEE 5th Conference on Engineering Education* (pp. 126-130). Kuala Lumpur: IEEE.

Bichsel, J. (2012). Analytics in higher education: Benefits, barriers, progress and recommendations. Retrieved from http://tinyurl.com/qf5xzhw.

Bobadilla, J., & Serradilla, F. (2009). The effect of sparsity on collaborative filtering metrics. In *Proceedings of the Twentieth Australasian Conference on Australasian Database-Volume 92* (pp. 9-18). Australian Computer Society, Inc..

Bobadilla, J., Ortega, F., Hernando, A., & Alcalá, J. (2011). Improving collaborative filtering recommender system results and performance using genetic algorithms. *Knowledge-based systems*, *24*(8), 1310-1316.

Bobadilla, J., Ortega, F., Hernando, A., & Gutiérrez, A. (2013). Recommender systems survey. *Knowledge-Based Systems, 46*, 109-132.

Bohannon, T. (2007). Predictive modelling in higher education. Retrieved from http://www2.sas.com/proceedings/forum2007/074-2007.pdf.

Bowles, T., Hattie, J., Dinham, S., Scull, J., & Clinton, J. (2014). Proposing a comprehensive model for identifying teaching candidates. *The Australian Educational Researcher, 41*(4), 365-380.

Bozo, J., Alarcón, R., & Iribarra, S. (2010). Recommending learning objects according to a teachers' context model. In M. Wolpers, P. A. Kirschner, M. Scheffel, S. Lindstaedt & V. Dimitrova (Eds.), *Sustaining TEL: From innovation to learning and practice* (pp. 470-475). Berlin Heidelberg: Springer.

Bramucci, R. & Gaston, J. (2012). SHERPA: Increasing student success with a recommendation engine. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 82–83). New York: ACM.

Breiter, A., & Light, D. (2006). Data for School Improvement: Factors for designing effective information systems to support decision-making in schools. *Educational Technology & Society, 9*(3), 206-217.

Brusilovsky, P., Karagiannidis, C., & Sampson, D. (2004). Layered evaluation of adaptive learning systems. *International Journal of Continuing Engineering Education and Life Long Learning*,*14*(4-5), 402-421.

Brusilovsky, P., & Millán, E. (2007). User models for adaptive hypermedia and adaptive educational systems. In P. Brusilovsky, A. Kobsa, & W. Nejdl (Eds.) *The adaptive web* (pp. 3-53). Springer-Verlag.

Brusilovsky, P., Cassel, L. N., Delcambre, L. M., Fox, E. A., Furuta, R., Garcia, D. D., ... & Yudelson, M. (2010). Social navigation for educational digital libraries. *Procedia Computer Science*, *1*(2), 2889-2897.

Buckingham Shum, S., & Ferguson, R. (2012). Social learning analytics. *Educational Technology & Society*, *15*(3), 3–26.

Burke, R. (2002). Hybrid recommender systems: Survey and experiments. *User modeling and user-adapted interaction*, *12*(4), 331-370.

Burke, R. (2007). Hybrid web recommender systems. In P. Brusilovsky, A. Kobsa, & W. Nejdl (Eds.) *The adaptive web* (pp. 377-408). Springer Berlin Heidelberg.

Bush, T. (2008). From Management to Leadership: Semantic or Meaningful Change?. *Educational Management, Administration and Leadership, 36*(2), 271–288.

Bush, T., & Glover, D. (2003). *School Leadership: Concepts and Evidence*. Nottingham: National College for School Leadership.

Bush, T., & Glover, D. (2012). Distributed leadership in action: Leading high-performing leadership tams in English schools. *School leadership & Management*, *32*(1), 21-36.

Bush, T., & Glover, D. (2014). School leadership models: what do we know?. *School leadership & Management*, *34*(5), 553-571.

Campbell, J. P. & Oblinger, D. G. (2007). *Academic analytics*. Retrieved from https://net.educause.edu/ir/library/pdf/PUB6101.pdf.

Campbell, J. P., DeBlois, P. B., & Oblinger, D. G. (2007). Academic analytics: A new tool for a new area. *EDUCAUSE Review*, *42*(4), 41-57.

Candillier, L., Meyer, F., & Boullé, M. (2007). Comparing state-of-the-art collaborative filtering systems. In P. Perner, & M., Petrou (Eds.) *International Workshop on Machine Learning and Data Mining in Pattern Recognition* (pp. 548-562). Springer Berlin Heidelberg.

Cavanagh, R.F., & Dellar, G.B. (1996). *School cultural elements questionnaire*. Unpublished PhD Dissertation, Curtin University, Perth.

CCSSO (Council of Chief State School Officers) (2014). Interstate School Leaders Licensure Consortium (ISLLC) Standards (Draft For Public Comment). [online] Retrieved from http://tinyurl.com/ly2t74q

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning, 4*(5), 318-331.

Chatti, M. A., Lukarov, V., Thüs, H., Muslim, A., Yousef, A. M. F., Wahid, U., Greven, C., Chakrabarti, A., Schroeder, U. (2014). Learning analytics: Challenges and future research directions. *Eleed, 10*.

Cheetham, G., & Chivers, G. (2005). *Professions, competence, and informal learning*. Cheltenham. UK: Edward Elgar Publishing

Chrysafiadi, K., & Virvou, M. (2013). Student modeling approaches: A literature review for the last decade. *Expert Systems with Applications, 40*(11), 4715-4729.

Clow, D. (2013a). An overview of learning analytics. *Teaching in Higher Education, 18*(6), 683–695.

Clow, D. (2013b). MOOCS and the funnel of participation. In *Proceedings of the 3rd Conference on Learning Analytics and Knowledge* (pp. 185-189). Leuven: ACM.

Cobos, C., Rodriguez, O., Rivera, J., Betancourt, J., Mendoza, M., LeóN, E., & Herrera-Viedma, E. (2013). A hybrid system of pedagogical pattern recommendations based on singular value decomposition and variable data attributes. *Information Processing & Management*, *49*(3), 607-625.

Coburn, C.E., & Turner, E.O. (2011). Research on data use: A framework and analysis. *Measurement: Interdisciplinary Research & Perspective, 9*(4), 173-206.

Coffrin, C., Corrin, L., de Barba, P., & Kennedy, G. (2014). Visualizing patterns of student engagement and performance in MOOCS. In *Proceedings of the 4th International Conference on Learning Analytics And Knowledge* (pp. 83-92). Indianapolis: ACM.

Cosic, R., Shanks, G., & Maynard, S. (2012). Towards a business analytics capability maturity model. In *Proceedings of the 23rd Australasian Conference on Information Systems* 2012 (pp. 1-11). Geelong: AAIS.

Copland, M.A., & Knapp, M.S. (2006). *Connecting leadership with learning: A framework for reflection, planning, and action.* ASCD.

Copland, M.A., Knapp, M.S., & Swinnerton, J.A. (2009). Principal Leadership, Data, and School Improvement. In T. Kowalski, & T.J. Lasley II (Eds.), *Handbook of Data-Based Decision Making in Education* (pp. 153-172), NY: Routledge.

Cox. B., & Jantti, M. (2012). Discovering the impact of library use and student performance. *EDUCAUSE Review, 47*(4), 1-9.

Cranston, N. (2013). School leaders leading professional responsibility not accountability as the key focus. *Educational Management Administration & Leadership, 41*(2), 129-142.

Crawford, V. M., Schlager, M., Penuel, W. R., & Toyama, Y. (2008). Supporting the art of teaching in a data-rich, high performance learning environment. In B. Mandinach & M. Honey (Eds.)*, Data-driven school improvement: Linking data and learning* (pp. 109-129).

Crowther, F., Ferguson, M., & Hann, L. (2009). *Developing Teacher Leaders: How Teacher Leadership Enhances School Success* (2nd Edition). Thousand Oaks: Corwin Press.

Dahlkemper, L. (2002). School board leadership: Using data for school improvement. *National School Board Association Research Policy Brief, 2*(1).

Dana N.F, & Yendol-Hoppey, D. (2014). *The reflective educator's guide to classroom research: Learning to teach and teaching to learn through practitioner inquiry*. Corwin Press, London

Daniel, B. (2015). Big data and analytics in higher education: Opportunities and challenges. *British Journal of Educational Technology, 46*(5), 904-920.

Davenport, T, Harris, J, & Morison, R. (2010). *Analytics at work*. Harvard: Harvard Business School Publishing Corporation.

Davies, S., & Pittard, V. (2009). *Harnessing technology review 2009. The role of technology in education and skills.* [online] R etrieved from http://dera.ioe.ac.uk/1422/1/ becta_2009_htreview_report.pdf

Davis, N., Eickelmann, B., & Zaka, P. (2013). Restructuring of educational systems in the digital age from a co-evolutionary perspective. *Journal of Computer Assisted Learning, 29*(5), 438-450.

Dawson, S., Bakharia, A., & Heathcote, E. (2010) SNAPP: Realising the affordances of real-time SNA within networked learning environments. In *Proceedings of the 7th International Conference on Networked Learning* (pp. 125-133). Aalborg.

Dawson, S., & Siemens, G. (2014). Analytics to literacies: The development of a learning analytics framework for multiliteracies assessment. *International Review of Research in Open and Distance Learning*, *15(*4*)*, 284-305.

Day, C., & Harris, A. (2002). Teacher Leadership, Reflective Practice and School Improvement. In Leithwood K & Hallinger P (Eds) *Second International Handbook of Educational Leadership and Administration* (pp. 957-977), Dordrecht: Kluwer Academic.

De Gemmis, M., Iaquinta, L., Lops, P., Musto, C., Narducci, F., & Semeraro, G. (2010). Learning preference models in recommender systems. In*Preference Learning* (pp. 387-407). Springer Berlin Heidelberg.

Detert, J. R., Schroeder, R. G., & Cudeck, R. (2003). The measurement of quality management culture in schools: development and validation of the SQMCS. *Journal of Operations Management, 21(*3*)*, 307-328.

Freitas, S., Gibson, D., Du Plessis, C., Halloran, P., Williams, E., Ambrose, M., ... & Arnab, S. (2015). Foundations of dynamic learning analytics: Using university student data to increase retention. *British Journal of Educational Technology*, *46*(6), 1175-1188.

Dhillon, G. (2008). Organizational competence for harnessing IT: A case study. *Information & Management, 45(*5*)*, 297-303

Diaz, V, & Brown, M. (2012). Learning analytics: A report on the ELI focus session. Retrieved from https://net.educause.edu/ir/library/PDF/ELI3027.pdf.

Dietz-Uhler, B., & Hurn, J. (2013). Using learning analytics to predict (and improve) student success: A faculty perspective. *Journal of Interactive Online Learning, 12(*1*)*, 17-26.

Digital School of Distinction (2016). *Digital Schools of Distinction*. [online] Retrieved from http://www.digitalschools.ie/criteria/

Dimmock, C. (2012). *Leadership, Capacity Building and School Improvement: Concepts, Themes and Impact*. Routledge: London.

Dimopoulos, I., Petropoulou, O., & Retalis, S. (2013). Assessing students' performance using the learning analytics enriched rubrics. In *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (pp. 195-199). Leuven: ACM.

Doyle, D. P. (2003). Data-driven decision-making: Is it the mantra of the month or does it have staying power?. *Technological Horizons In Education Journal*, *30*(10).

Doz, Y. (1997). Managing Core Competeney for Corporate Renewal: TO\vards a Managerial Theory of Core Competeneies. In A. Campbell and K. Sommers Luchs. (1997), *Core Competency-based Strategy* (pp. 53-75). London: International Thompson Business Press.

Drachsler, H., Pecceu, D., Arts, T., Hutten, E., Rutledge, L., Van Rosmalen, P., ... & Koper, R. (2009). ReMashed–recommendations for mash-up personal learning environments. In*European Conference on Technology Enhanced Learning* (pp. 788-793). Springer Berlin Heidelberg.

Drachsler, H., Verbert, K., Santos, O. C., & Manouselis, N. (2015). Panorama of recommender systems to support learning. In F. Ricci, L. Rokach, & B. Shapira (Eds.) *Recommender systems handbook* (pp. 421-451). Springer US.

Drejer, A. (2000). Organisational learning and competence development. *The Learning Organization, 7(*4*)*, 206-220.

Dron, J., Mitchell, R., Siviter, P., & Boyne, C. (2000). CoFIND—an experiment in N-dimensional collaborative filtering. *Journal of Network and Computer Applications*, *23*(2), 131-142.

Duncan-Howell, J. (2010). Teachers making connections: Online communities as a source of professional learning. *British Journal of Educational Technology, 41(*2*)*, 324-340

Dunn, K. E., Airola, D. T., Lo, W. J., & Garrison, M. (2013). What teachers think about what they can do with data: Development and validation of the data driven decision-making efficacy and anxiety inventory. *Contemporary Educational Psychology, 38*(1), 87-98.

Durando, M., Blamire, R., Balanskat, A., & Joyce, A. (2007). *E-mature schools in Europe*. [online] Retrieved from http://tinyurl.com/ncxrhgr

Duval, E., & Verbert, K. (2012). Learning Analytics. *Eleed, 8*.

Dyckhoff, A. L., Zielke, D., Bültmann, M., Chatti, M. A., & Schroeder, U. (2012). Design and implementation of a learning analytics toolkit for teachers. *Educational Technology & Society, 15(*3*)*, 58–76.

Dyckhoff, A. L., Lukarov, V., Muslim, A., Chatti, M. A., & Schroeder, U. (2013). Supporting action research with learning analytics. In *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (pp. 220-229). Leuven: ACM.

Dziuban, C., Moskal, P., Cavanagh, T., & Watts, A. (2012). Analytics that inform the university: Using data you already have. *Journal of Asynchronous Learning Networks, 16*(3), 21–38.

Earley, P. (2012). *Standards for school leaders: competency frameworks and their applicability*. European Policy Network for School Leadership. [online] Retrieved from http://tinyurl.com/mjkpnoh

Earl, L., & Katz, S. (2006). *Leading Schools In A Data Rich World*. Thousand Oaks, CA: Corwin Press.

Edgar, W. B., & Lockwood, C. A. (2008). Organizational competencies: clarifying the construct. *Journal of Business, 22*, 21-32.

El Helou, S., Salzmann, C., & Gillet, D. (2010). The 3A Personalized, Contextual and Relation-based Recommender System. *J. UCS*, *16*(16), 2179-2195.

Ermilova , E., & Afsarmanesh, H. (2007). Competency and profiling management in virtual organization breeding environments. In L. M. Camarinha-Matos, H. Afsarmanesh, & M. Ollus (Eds.), *Network-Centric Collaboration and Supporting Frameworks* (pp. 131–142), NY: Springer.

European Commission (2010). Learning, Innovation and ICT. Lessons learned by the ICT cluster Education & Training 2010 programme. [online] Retrieved from http://tinyurl.com/ny5zhnn

European Commission (2011). *Key Data on Learning and Innovation through ICT at School in Europe 2011* [online] Retrieved from http://tinyurl.com/kecagv7

European Commission / EACEA / Eurydice (2012). *Developing Key Competences at School in Europe: Challenges and Opportunities for Policy*. *Eurydice Report*. Luxembourg: Publications Office of the European Union [online] Retrieved from http://eacea.ec.europa.eu/education/eurydice/documents/thematic_reports/145EN.pdf

European Commission (2012). Supporting the Teaching Professions for Better Learning Outcomes. [online] Retrieved from http://tinyurl.com/ndbjhbo

European Commission (2013). Survey of Schools: ICT in Education Benchmarking Access, Use and Attitudes to Technology in Europe's Schools. [online] Retrieved from http://tinyurl.com/nqvhw9a

European Commission (2013b). Supporting teacher competence development for better learning outcomes. [online] Retrieved from http://goo.gl/CZJHsj

European Commission (2015). Assuring Quality in Education: Policies and Approaches to School Evaluation in Europe. Retrieved from http://tinyurl.com/jul3qsu

European Schoolnet (2009). *Learning from each other: the p2v project on ict and school change* [online]. Retrieved from http://peerlearning.eun.org/shared/data/pdf/ p2v_book_final.pdf

Fazeli, S., Drachsler, H., Brouns, F., & Sloep, P. (2014). Towards a social trust-aware recommender for teachers. In N. Manouselis, H. Drachsler, K. Verbert & O. C. Santos (Eds.), *Recommender Systems for Technology Enhanced Learning* (pp. 177-194). New York: Springer.

Ferreira, S. A., & Andrade, A. (2014). Academic Analytics: Anatomy Of An Exploratory Essay. *Education and Information Technologies*, 1-15

Ferreira-Satler, M., Romero, F. P., Menendez-Dominguez, V. H., Zapata, A., & Prieto, M. E. (2012). Fuzzy ontologies-based user profiles applied to enhance e-learning activities. *Soft Computing*, *16*(7), 1129-1141.

Fessakis, G., Dimitracopoulou, A., & Palaiodimos, A. (2013). Graphical interaction analysis impact on groups collaborating through blogs. *Educational Technology & Society, 16*(1), 243–253.

Firestone, W.A.., & Martinez, M.C. (2009).Districts, School Leaders and Distributed Leadership: Changing Intructional Practice. In K. Leithwood, B. Mascall, & T. Strauss (Eds). *Distributed Leadership According to the Evidence* (pp.61-86). New York: Routledge.

Forsythe, Jr., R. G., Chacon, F. J., Spicer, D. Z., & Valbuena, A. (2012). Two case studies of learner analytics in the university system of Maryland. Retrieved from http://www.educause.edu/ero/article/two-case-studies-learner-analytics-university-system-maryland

Frankfort, J., Salim, K., Carmean, C., & Haynie, T. (2012). Analytics, nudges, and learner persistence. Retrieved from www.educause.edu/ero/article/analytics-nudges-and-learner-persistence.

Freiling, J. (2004). A Competence-based Theory of the Firm. management revue. *The International Review of Management Studies, 15(1)*, 27-52.

Fritz, J. (2011). Classroom walls that talk: Using online course activity data of successful students to raise self-awareness of underperforming peers. *The Internet and Higher Education, 14*(2), 89-97.

García-Barriocanal, E., Sicilia, M. A., & Sánchez-Alonso, S. (2012). Computing with competencies: Modelling organizational capacities. *Expert systems with applications, 39*(16), 12310-12318.

Garcia-Martinez, S., & Hamou-Lhadj, A. (2013). Educational recommender systems: A pedagogical-focused perspective. In G. Tsihrintzis., M. Virvou, L. Jain (Eds.) *Multimedia Services in Intelligent Environments* (pp. 113-124). Springer International Publishing.

García-Valdez, M., & Parra, B. (2009). A hybrid recommender system architecture for learning objects. In *Evolutionary Design of Intelligent Systems in Modeling, Simulation and Control* (pp. 205-211). Springer Berlin Heidelberg.

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59(1)*, 64-71.

Gašević, D., Kovanović, V., Joksimović, S., & Siemens, G. (2014). Where is research on massive open online courses headed? A data analysis of the MOOC Research Initiative. *The International Review of Research in Open and Distributed Learning, 15*(5), 134-176.

Gašević, D., Dawson, S., Rogers, T., & Gasevic, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education*, *28*, 68-84.

Gibson, D., & de Freitas, S. (2016). Exploratory analysis in learning analytics. *Technology, Knowledge and Learning*, *21*(1), 5-19.

Giesbers, B., Rienties, B., Tempelaar, D. T., & Gijselaers, W. H. (2013). Investigating the relations between motivation, tool use, participation, and performance in an e-learning course using web-videoconferencing. *Computers in Human Behavior, 29*(1), 285–292.

Gill, L. M. (2006). *Building organisational capability*. PhD Dissertation, Queensland University of Technology.

Gill, B., Borden, B.C., & Hallgren, K. (2014). A Conceptual Framework for Data-Driven Decision Making. *Mathematica Policy Research Report* [online] Retrieved from http://tinyurl.com/phwuglp

Goktas, Y., Gedik, N., & Baydas, O. (2013). Enablers and barriers to the use of ICT in primary schools in Turkey: A comparative study of 2005–2011. *Computers & Education, 68*, 211-222.

Goldstein, P.J., & Katz, R.N. (2005). Academic analytics: The uses of management information and technology in higher education. Retrieved from https://net.educause.edu/ir/library/pdf/ERS0508/ekf0508.pdf.

Goldstein, P.J., & Katz, R.N. (2005). Academic analytics: The uses of management information and technology in higher education. Retrieved from https://net.educause.edu/ir/library/pdf/ERS0508/ekf0508.pdf.

Gonzalez, R.A., & Firestone, W.A. (2013). Educational tug-of-war: internal and external accountability of principals in varied contexts. *Journal of Educational Administration*, *51*(3), 383 – 406.

Gonzales, S., & Lambert, L. (2014). Teacher leadership in professional development schools: Emerging conceptions, identities, and practices. *Journal of School Leadership, 11*(1), 6-24.

Govaerts, S., Verbert, K., Klerkx, J., & Duval, E. (2010). Visualizing activities for self-reflection and awareness. In X. Luo, M. Spaniol, L. Wang, Q. Li, W. Nejdl & W. Zhang

Grant, R. (1991), The resource-based theory of competitive advantage: implications for strategy. *California Management Review*, *33*, 114-135.

Gu, J. W., & Jung, H. W. (2013). The effects of IS resources, capabilities, and qualities on organizational performance: An integrated approach. *Information & Management, 50*, 87-97.

Gurr, D., & Drysdale, L. (2013). Middle-level secondary school leaders. *Journal of Educational Administration*, *51(*1), 55 – 71.

Graf, S., Ives, C., Rahman, N., & Ferri, A. (2011). AAT - A tool for accessing and analysing students' behaviour data in learning systems. In *Proceedings of the 1st International Conference on Learning Analytics and Knowledge* (pp. 174-179). Banff: ACM.

Greller, W., & Drachsler, H. (2012). Translating learning into numbers: A generic framework for learning analytics. *Educational Technology & Society, 15*(3), 42–57.

Gunn, C. (2014). Defining an agenda for learning analytics. In B. Hegarty, J. McDonald, & S.-K. Loke (Eds.), *Rhetoric and Reality: Critical perspectives on educational technology.* (pp. 683-687). Dunedin.

Hafeez, K., Zhang, Y., & Malak, N. (2002). Determining key capabilities of a firm using analytic hierarchy process. *International Journal Of Production Economics, 76(1)*, 39-51.

Hansen C.J., & Wasson, B. (2016). Teacher Inquiry into Student Learning:-The TISL Heart Model and Method for use in Teachers' Professional Development. *Nordic Journal of Digital Literacy, 10*(1), 24-49

Hauge, T. E., Norenes, S. O., & Vedøy, G. (2014). School leadership and educational change: Tools and practices in shared school leadership development. *Journal of Educational Change, 15*(4), 357-376

Harris, R. (2007). *Unravelling the notion of organisational capability: What do writers say it is and VET providers think it is*?. PhD dissertation, AVETRA

Harrison, C., Tomás, C., & Crook, C. (2014). An e-maturity analysis explains intention–behavior disjunctions in technology adoption in UK schools. *Computers in Human Behavior*, *34*, 345-351.

Helfat, C.E. (2003). Stylized facts regarding the evolution of organizational resources and capabilities. In Helfat, C.E. (ed.), *The SMS Blackwell handbook of organizational capabilities: emergence, development, and change* (pp. 1-11). Malden, MA: Blackwell Publishing.

Hendeghem, A. & Vendermeulen, F. (2000). Competency Management in the Flemish and Dutch Civil Service. *The International Journal of Public Sector Management, 13(4)*, 342-353

Hendriks, M. A., & Scheerens, J. (2013). School leadership effects revisited: a review of empirical studies guided by indirect-effect models. *School leadership & management, 33*(4), 373-394.

Herlocker, J., Konstan, J. A., & Riedl, J. (2002). An empirical analysis of design choices in neighborhood-based collaborative filtering algorithms. *Information retrieval*, *5*(4), 287-310.

Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Riedl, J. T. (2004). Evaluating collaborative filtering recommender systems. *ACM Transactions on Information Systems (TOIS)*,*22*(1), 5-53.

Hmelo-Silver, C. E., & Azevedo, R. (2006). Understanding complex systems: Some core challenges. *The Journal of the learning sciences, 15*(1), 53-61.

Hoel, T., & Grant, S. (2013). *Integrating Learning Outcomes and Competences* [online] Retrieved from http://wiki.teria.no/display/inloc/Scope+of+the+Model

Holland, J.H. (1998). *Emergence: From chaos to order*. Massachusetts: Perseus Books.

Hooge, E., Burns, T., & Wilkoszewski, H. (2012). *Looking Beyond the Numbers: Stakeholders and Multiple School Accountability*. OECD Education Working Papers, 85, OECD Publishing.

Houtveen, A.A.M., Voogt, J.C., Van der Vegt, A.L., & Van de Grift, W.J.C.M. (1996). *These Are Our Manners: Research into the Organizational Culture of Schools.* ISOR, Utrecht.

Howlin, C., & Lynch, D. (2014). Learning and academic analytics in the Realizeit system. In *Proceedings of the World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education* (pp. 862-872). New Orleans: AACE.

Hsieh, T. C., Wang, T. I., Su, C. Y., & Lee, M. C. (2012). A Fuzzy Logic-based Personalized Learning System for Supporting Adaptive English Learning. *Educational Technology & Society*,*15*(1), 273-288.

Huang, S., & Fang, N. (2013). Predicting student academic performance in an engineering dynamics course: A comparison of four types of predictive mathematical models. *Computers & Education, 61*, 133-145.

Huang, Z., Zeng, D., & Chen, H. (2007). A Comparison Of Collaborative-Filtering Recommendation Algorithms For e-Commerce. *IEEE Intelligent Systems, 22*(5), 68-78.

Huang, J., & Kapur, M.(2007). Diffusion of pedagogical innovations as a complex adaptive process: Agent-based modeling as research method. In *Proceedings of the 15th International Conference on Computers in Education* (pp. 67-74). Linz: Springer.

Huang, J., & Kapur, M. (2012). Learning innovation diffusion as complex adaptive systems through model building, simulation, game play and reflections. In J. van Aalst, K. Thompson, M. J. Jacobson & P. Reimann (Eds.), *Proceedings of the International Conference of the Learning Sciences (ICLS) 2012* (pp. 259-266). Sydney: ISLS.

Ice, P., Díaz, S., Swan, K., Burgess, M., Sharkey, M., Sherrill, J., ... & Okimoto, H. (2012). The PAR framework proof of concept: Initial findings from a multi-institutional analysis of federated postsecondary data. *Journal of Asynchronous Learning Networks, 16*(3), 63-86.

Ifenthaler, D. (2015). Learning analytics. In J. M. Spector (Ed.), *The SAGE Encyclopedia of educational technology* (pp. 447–451). Thousand Oaks, CA: Sage.

Ifenthaler, D., & Widanapathirana, C. (2014). Development and validation of a learning analytics framework: Two case studies using support vector machines. *Technology, Knowledge and Learning*, *19*(1-2), 221-240

Ikemoto, G. S., & Marsh, J. A. (2007). Cutting through the data-driven mantra: Different conceptions of data-driven decision making. In P. A. Moss (Ed.), *Evidence and decision making* (pp. 105-131). USA: Wiley-Blackwell.

ISTE (2009). *Standards for Administrators* [online] Retrieved from http://www.iste.org/docs/pdfs/20-14_ISTE_Standards-A_PDF.pdf

Javidan, M. (1998). Core competence: what does it mean in practice?. *Long range planning, 31(1)*, 60-71.

Jayaprakash, S. M., Moody, E. W., Lauría, E. J., Regan, J. R., & Baron, J. D. (2014). Early alert of academically at-risk students: An open source analytics initiative. *Journal of Learning Analytics, 1*(1), 6-47.

Joksimović, S., Gašević, D., Loughin, T. M., Kovanović, V., & Hatala, M. (2015). Learning at distance: Effects of interaction traces on academic achievement. *Computers & Education*,*87*, 204-217.

Johnson, L., Adams Becker, S., Estrada, V., & Freeman, A. (2014). NMC horizon report: 2014 K-12 edition. Retrieved from http://tinyurl.com/om7l4dn.

Junco, R., & Clem, C. (2015). Predicting course outcomes with digital textbook usage data. *The Internet and Higher Education*, *27*, 54-63.

Kampylis, P., Punie, Y. & Devine, J. (2015); Promoting Effective Digital-Age Learning - A European Framework for Digitally-Competent Educational Organisations. Retrieved from http://tinyurl.com/jfwo8yq

Kaufman, T. E., Graham, C. R., Picciano, A. G., Popham, J. A., & Wiley, D. (2014). Data-Driven Decision Making in the K-12 Classroom. In J.M. Spector, M.D. Merrill, J. Elen, & M.J. Bishop, (Eds.) *Handbook of Research on Educational Communications and Technology* (pp. 337-346). New York: Springer

Kizilcec, R. F., Piech, C., & Schneider, E. (2013). Deconstructing disengagement: Analyzing learner subpopulations in massive open online courses. In *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (pp. 170-179). Leuven: ACM.

Knapp, M. S., Swinnerton, J. A., Copland, M. A., & Monpas-Huber, J. (2006). Data-Informed Leadership in Education. Center for the Study of Teaching and Policy. [online] Retrieved from http://tinyurl.com/qa39v34

Knapp, M., & Feldman, S. (2012). Managing the intersection of internal and external accountability: Challenge for urban school leadership in the United States. *Journal of Educational Administration, 50(*5*)*, 666 - 694.

Koehler, M., & Mishra, P. (2009). What is technological pedagogical content knowledge (TPACK)?. *Contemporary issues in technology and teacher education, 9*(1), 60-70.

Kraaijenbrink, J, Spender, le., & Groen, AJ. (2010). The Resource-based View: A Review and Assessment of its Critiques*. Journal of Management. 36(*1*)*, 349-372

Lai, M.K., & Hsiao, S. (2014). Developing data collection and management systems for decision-making: What professional development is required?. *Studies in Educational Evaluation, 42*, 63-70.

Lai, M.K., & Schildkamp, K. (2013). Data-based Decision Making: An Overview. In K. Schildkamp, M.K. Lai, L. Earl (eds.), *Data-based Decision Making in Education* (pp. 9-21), Dordrecht: Springer.

Larusson, J.A., & White, B. (2012). Monitoring student progress through their written 'point of originality'. In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge* (pp. 212-221). New York: ACM.

Lauría, E. J. M., Baron, J. D., Devireddy, M., Sundararaju, V., & Jayaprakash, S. M. (2012). Mining academic data to improve college student retention: An open source perspective. In *Second International Conference on Learning Analytics and Knowledge* (pp. 139–142) Vancouver: ACM.

Laurillard, D. 2007. Modelling benefits-oriented costs for technology enhanced learning. *Higher Education*, *54(*1*)*, 21–39

Law, N., & Chow, A. (2008). Teacher characteristics, contextual factors, and how these affect the pedagogical use of ICT. In L. Nancy, P. Willem J. and P. Tjeerd (Eds.), *Pedagogy and ICT Use in Schools around the World* (pp. 181-219). Netherlands: Springer

Le Deist, F., & Winterton, J. (2005), What is competence?, *Human Resource Development International, 8(*1*)*, 27-46.

Leithwood, K., Day, C., Sammons, P., Harris, A., & Hopkins, D. (2006). *Successful School Leadership What It Is and How It Influences Pupil Learning*. Department for Education and Skills: National College for School Leadership [online] Retrieved from http://tinyurl.com/ouha9k8

Lejeune, C. (2006). Organizational *learning and capabilities: An integrative conceptual framework* [online] Retrieved from http://www.uclouvain.be/cps/ucl/doc/iag/documents/WP_6_Lejeune.pdf

Lichtenstein, B. B., Uhl-Bien, M., Marion, R., Seers, A., Orton, J. D., & Schreiber, C. (2006). Complexity leadership theory: An interactive perspective on leading in complex adaptive systems. *Emergence: Complexity & Organization, 8*(4), 2-12.

Limongelli, C., Miola, A., Sciarrone, F., & Temperini, M. (2012). Supporting teachers to retrieve and select learning objects for personalized courses in the moodle_ls environment. In *2012 IEEE 12th International Conference on Advanced Learning Technologies*(pp. 518-520). IEEE.

Liou, Y., Grigg, J., & Halverson, R. (2014). Leadership and the Design of Data driven Professional Networks in Schools. *Journal of Educational Leadership and Management*, *2*(1), 29-73.

Liu, D. Y. T., Froissard, J. C., Richards, D., & Atif, A. (2015). An enhanced learning analytics plugin for Moodle: student engagement and personalised intervention. In *Proceedings of the 2015 ASCILITE Conference* (pp. 180-189)

Lockyer L., Heathcote E., & Dawson S. (2013). Informing pedagogical action: Aligning learning analytics with learning design. *American Behavioral Scientist, 57*(10), 1439-1459

Long, P., & Siemens, G. (2011). Penetrating the fog: Analytics in learning and education. *Educause Review, 46*(5), 30-32.

Lops, P., De Gemmis, M., & Semeraro, G. (2011). Content-based recommender systems: State of the art and trends. In F. Ricci, L. Rokach, B. Shapira, & P. B. Kantor (Eds.), *Recommender systems handbook* (pp. 73-105). Springer US.

Jung, T., Scott, T., Davies, H. T. O., Bower, P., Whalley, D., McNally, R., et al. (2007). *Instruments for the Exploration of Organisational Culture* [online] Retrieved from http://www.scothub.org/culture/instruments.html

Luger, J. (2007). *NIACE report: Supporting the journey towards E-Maturity* [online]. Retrieved from: http://archive.excellencegateway.org.uk/media/ferl_and_aclearn/acl/

Lykourentzou, I., Giannoukos, I., Nikolopoulos, V., Mpardis, G., & Loumos, V. (2009). Dropout prediction in e-learning courses through the combination of machine learning techniques. *Computers & Education, 53*(3), 950-965.

Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. *Computers & Education, 54*(2), 588-599.

Macfadyen, L., & Dawson, S. (2012). Numbers are not enough. Why e-learning analytics failed to inform an institutional strategic plan. *Educational Technology & Society, 15*(3), 149-163.

Macfadyen, L. P., Dawson, S., Pardo, A., & Gasevic, D. (2014). Embracing big data in complex educational systems: The learning analytics imperative and the policy challenge. *Research & Practice in Assessment, 9*(2), 17-28.

Mandinach, E. (2012). A Perfect Time for Data Use: Using Data driven Decision Making to Inform Practice. *Educational Psychologist, 47*(2), 71-85.

Mandinach, E., & Gummer, E. (2013). A systemic view of implementing data literacy in educator preparation. *Educational Researcher, 42*, 30–37.

Mandinach, E., & Gummer, E. (2015). Data-Driven Decision Making: Components of the Enculturation of Data Use in Education. *Teachers College Record, 117*(4), 1-8.

Manouselis, N., Vuorikari, R., & Van Assche, F. (2010). Collaborative recommendation of e-learning resources: an experimental investigation. *Journal of Computer Assisted Learning*, *26*(4), 227-242.

Manouselis, N., Drachsler, H., Verbert, K., & Duval, E. (2013). TEL as a Recommendation Context. In N. Manouselis, H. Drachsler, K. Verbert, & E. Duval (Eds.), *Recommender Systems for Learning* (pp. 21-36). New York: Springer.

Manouselis, N., Drachsler, H., Vuorikari, R., Hummel, H., & Koper, R. (2011). Recommender Systems In Technology Enhanced Learning. In F. Ricci, L. Rokach, B. Shapira, & P. B. Kantor (Eds.), *Recommender systems handbook* (pp. 387-415). New York: Springer.

Manouselis, N., Karagiannidis, C., & Sampson, D. G. (2014). Layered evaluation in recommender systems: a retrospective assessment. *Journal of e-Learning and Knowledge Society*, *10*(1).

Marin, L., Isern, D., & Moreno, A. (2013a). Dynamic adaptation of numerical attributes in a user profile.*Applied intelligence*, *39*(2), 421-437.

Marin, L., Isern, D., Moreno, A., & Valls, A. (2013b). On-line dynamic adaptation of fuzzy preferences. *Information Sciences*, *220*, 5-21.

Marin, L., Moreno, A., & Isern, D. (2014). Automatic preference learning on numeric and multi-valued categorical attributes. *Knowledge-Based Systems*, *56*, 201-215.

Maritan, C.A. (2001). Capital investment as investing in organizational capabilities: an empirically grounded process model. *Academy of Management Journal, 44*, 513–531.

Marsh, J. A., Pane, J. F., & Hamilton, S. (2006). *Making sense of data driven decision making in education: Evidence from recent RAND research*. Santa Monica, CA: RAND Corporation

Marsh, J. A., & Farrell, C.C. (2014). How leaders can support teachers with data-driven decision making A framework for understanding capacity building. *Educational Management Administration & Leadership*, 1-21.

Marshall, S. (2007). *E-Learning Maturity Model: Process Descriptions*. [online] Retrieved from: http://www.utdc.vuw.ac.nz/research/emm/documents/versiontwothree/ 20070620ProcessDescriptions.pdf

Martelo, S., Barroso, C., & Cepeda, G. (2013). The use of organizational capabilities to increase customer value. *Journal of Business Research. 66(*10*)*, 2042–2050.

Maslowski, R. (2006). A review of inventories for diagnosing school culture. *Journal of Educational Administration, 44(*1*)*, 6-35.

McKenney S., Mor Y. (2015). Supporting teachers in data-informed educational design. *British Journal of Educational Technology, 46*(2):265-279

McQuillan, P. (2008). Small school reform through the lens of complexity theory. *Teachers College Record, 110*(9), 1772-1801.

Means, B., Padilla, C., & Gallagher, L. (2010). *Use of education data at the local level from accountability to instructional improvement*. Report prepared for U.S. Department of Education, Office of Planning, Evaluation and Policy Development [online] Retrieved from http://tinyurl.com/mcvtwss

Micheuz, P. (2009). E-Maturity and School Development: When the Tail Wants to Wag the Dog. In A. Tatnall, & A. Jones (Eds.) *Education and Technology for a Better World* (pp. 129-137). Berlin Heidelberg: Springer

Miller, J., & Page, S. (2007). *Complex adaptive systems: An introduction to computational models of social life*. Princeton: Princeton University Press.

Mital, P., Moore, R., & Llewellyn, D. (2014). Analyzing K-12 Education as a complex system. *Procedia Computer Science, 28*, 370-379

Moridis, C. N., & Economides, A. A. (2009). Prediction of student's mood during an online test using formula-based and neural network-based method. *Computers & Education, 53*(3), 644-652.

Morrison, K. (2010). Complexity theory, school leadership and management: questions for theory and practice. *Educational Management Administration & Leadership, 38*(3), 374-393

Mourshed, M., Chijioke, C., & Barber, M. (2010). *How the world's most improved school systems keep getting better*. London: McKinsey & Company.

Mottus, A., Kinshuk, Graf, S., & Chen, N.-S. (2015). Use of Dashboards and Visualization Techniques to Support Teacher Decision Making. In Kinshuk, & R. Huang (Eds.), *Ubiquitous Learning Environments and Technologies, Lecture Notes in Educational Technology* (pp. 181 – 199), Berlin Heidelberg: Springer.

Mulford, B. (2003). School leaders: Challenging roles and impact on teacher and school effectiveness. Paris: Commissioned paper by the Education and Training Policy Division, OECD [online] Retrieved from http://www.oecd.org/edu/school/37133393.pdf

Murray, J. (2013). Critical issues facing school leaders concerning data informed decision-making. *School Leadership & Management, 33*(2), 169-177.

Murray, P. & Donegan, K. (2003). Empirical Linkages between Firm Competencies and Organizational Learning. *The Learning Organization, 10(*1*)*, 51-62.

NAACE (2012). *Naace: self-review framework*. [online] Retrieved from: http://www.naace.co.uk/ictmark/srf

Nachmias, R., Mioduser, D., Cohen, A., Tubin, D., & Forkosh-Baruch, A. (2004). Factors involved in the implementation of pedagogical innovations using technology. *Education and Information Technologies*, *9*(3), 291-308.

NEA (National Education Association) (2014). *The Teacher Leadership Competencies*. [online] Retrieved from http://tinyurl.com/p4dto9e

New Media Consortium (2014). *Horizon Report > 2014 K-12 Edition* [online] Retrieved from http://cdn.nmc.org/media/2014-nmc-horizon-report-k12-EN.pdf

Norris, D., Baer, L., Leonard, J., Pugliese, L., & Lefrere, P. (2008). Action analytics: Measuring and improving performance that matters in higher education. *EDUCAUSE Review*, *43*(1), 42-67.

Norris, D., & Baer, L. (2013). Building organizational capacity for analytics. Retrieved from https://net.educause.edu/ir/library/pdf/PUB9012.pdf.

Norris, D., Baer, L., & Offerman, M. (2009). A national agenda for action analytics. Retrieved from http://tinyurl.com/mqlcvuo.

Nogueira, A. C., & Bataglia, W. (2012). Transaction Costs and Organizational Competences: Explaining the Governance Structure for Manufacturing Stage. *Journal of Technology Management & Innovation, 7(*1*)*, 159-174.

OECD (2008). *Improving School Leadership Volume 1: Policy And Practice*. [online] Retrieved from http://www.oecd.org/education/school/44374889.pdf

OECD (2009). *Teacher Evaluation A Conceptual Framework and examples of Country Practices*. [online] Retrieved from http://www.oecd.org/education/school/44568106.pdf

OECD (2010). *Inspired by Technology, Driven by Pedagogy: A Systemic Approach to Technology-Based School Innovations* [online] Retrieved from http://tinyurl.com/3bv2wlq

OECD (2011). *Well-being at school: does infrastructure matter?*. [online] Retrieved from http://tinyurl.com/ozzkwqc.

OECD (2013a), Innovative Learning Environments. Educational Research and Innovation. OECD Publishing

OECD (2013b). The International Benchmarking for School Improvement. OECD Publishing. Retrieved from http://tinyurl.com/jhdzk9d

OECD (2013c). *Leadership for 21st Century Learning*. OECD Publishing. [online] Retrieved from http://www.oecd-ilibrary.org/education/leadership-for-21st-century-learning_9789264205406-en.

OECD (2014a). *Education at a Glance 2014: OECD Indicators*. OECD Publishing. [online] Retrieved from http://www.oecd.org/edu/Education-at-a-Glance-2014.pdf

OECD (2014b). *School Improvement Through Strong Leadership*. [online] Retrieved from http://tinyurl.com/k62u4sc

OECD (2015a). Students, Computers and Learning Making the Connection. OECD Publishing. Retrieved from http://tinyurl.com/orowjtm

OECD (2015b). Education Policy Outlook 2015: Making Reforms Happen. OECD Publishing. Retrieved from http://tinyurl.com/htwr97k

Olson, D. (2008). Multi-Criteria Decision Support. In F. Burstein, & C.W. Holsapple (Eds.), *Handbook on Decision Support Systems 1: Basic Themes* (pp. 299-314). Berlin Heidelberg: Springer.

OpenLearn, (2006). Understanding organisational capabilities [online] Retrieved from http://www.open.edu/openlearn/money-management/management/human-resources/strategic-view-performance/content-section-3.1

Ossege, C. (2012). Accountability – are We Better off Without It? An empirical study on the effects of accountability on public managers' work behaviour. *Public Management Review, 14(*5*)*, 585-607.

Oswald, M., & Engelbrecht, P. (2013). Leadership in disadvantaged primary schools: Two narratives of contrasting schools. *Educational Management Administration & Leadership, 41*(5), 620–639.

Pang, N.S.K. (1998). The binding forces that hold school organizations together. *Journal of Educational Administration, 36(*4*)*, 314-33

Papamitsiou, Z., & Economides, A. (2014). Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence. *Educational Technology & Society, 17(*4*)*, 49–64.

Pardos, Z. A., Baker, R. S., San Pedro, M. O., Gowda, S. M., & Gowda, S. M. (2013). Affective states and state tests: Investigating how affect throughout the school year predicts end of year learning outcomes. In *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (pp. 117-124). Leuven: ACM.

Park, V., & Datnow, A. (2009). Co-constructing distributed leadership: district and school connections in data driven decision-making. *School Leadership & Management*, *29(*5), 477-494.

Peña-Ayala, A. (2014). Educational data mining: A survey and a data mining-based analysis of recent works. *Expert Systems with Applications, 41*(4), 1432–1462.

Peña-López, I. (2015). *Students, Computers and Learning. Making the Connection*. OECD Publishing

Pelgrum, W. J. (2008). School practices and conditions for pedagogy and ICT. In N. Law, W. J. Pelgrum, & T. Plomp (Eds.), *Pedagogy and ICT use in schools around the world. Findings from the IEA SITES 2006 study,* pp. 67–121. Hong Kong: Springer

Petropoulou, O., Kasimatis, K., Dimopoulos, I., & Retalis, S. (2014). LAe-R: A new learning analytics tool in Moodle for assessing students' performance. *Bulletin of the IEEE Technical Committee on Learning Technology, 16*(1), 2-5.

Phillips, R., Preston, G., Roberts, P., Cumming-Potvin, W., Herrington, J., Maor, D., & Gosper, M. (2010). Using academic analytic tools to investigate studying behaviours in technology-supported learning environments. In *Proceedings of the 2010 Ascilite Conference* (pp. 761-771). Sydney.

Picciano, A. (2009). Developing and Nurturing Resources for Effective Data-Driven Decision Making. In T. Kowalski, & T.J. Lasley II (Eds.), *Handbook of Data-Based Decision Making in Education* (pp. 123-135), NY: Routledge.

Pick, R.A. (2008). Benefits of Decision Support Systems. In F. Burstein, & C.W. Holsapple (Eds.), *Handbook on Decision Support Systems 1: Basic Themes* (pp. 719 - 730). Berlin Heidelberg: Springer.

Piety, P. J., Hickey, D. T., & Bishop, M. J. (2014). Educational data sciences: Framing emergent practices for analytics of learning, organizations, and systems. In *Proceedings of the 4th International Conference on Learning Analytics And Knowledge* (pp. 193-202). Indianapolis: ACM.

Pirani, J. A., & Albrecht, B. (2005). University of Phoenix: Driving decisions through academic analytics. Retrieved from http://tinyurl.com/nom3j7f.

Pistilli, M. D., Willis III, J. E., & Campbell, J. P. (2014). Analytics through an institutional lens: definition, theory, design, and impact. In J. A. Larusson & B. White (Eds.), *Learning Analytics* (pp. 79-102). New York: Springer

Portin, B.S. (2005). School-Based Leadership in the US in an Age of Reform: What Does it Take?. *Education Research and Perspectives*, *32*(2), 1-23.

Power, D. (2008a). Decision Support Systems: A Historical Overview. In F. Burstein, & C.W. Holsapple (Eds.), *Handbook on Decision Support Systems 1: Basic Themes* (pp. 121-140) .Berlin Heidelberg: Springer

Power, D. (2008b). Understanding Data-Driven Decision Support Systems. *Information Systems Management, 25*(2), 149-154

Prahalad, C. K., & Hamel, G. (1990). *The core competence of the corporation*. Boston (MA).

Qi, X. (2010). Research on user profiling technology for personalized demands. In*Intelligent Computation Technology and Automation (ICICTA), 2010 International Conference on* (Vol. 3, pp. 198-201). IEEE.

Rafaeli, S., Barak, M., Dan-Gur, Y., & Toch, E. (2004). QSIA–a web-based environment for learning, assessing and knowledge sharing in communities. *Computers & Education, 43*(3), 273-289.

Rakickaite, J., Juceviciene, P., & Vaitkiene, R. (2011). Structure of Professional Service Firm's Organizational Competence. *Social Sciences, 73(*3*)*, 51-61.

Ravishanker, G. (2011). Doing academic analytics right: Intelligent answers to simple questions. *Educause Review, 2*, 1–11.

Rhee, C., & Rao, R. (2008). Evaluation of Decision Support Systems. In F. Burstein & C.W. Holsapple (Eds.), *Handbook on Decision Support Systems 2: Variations* (pp. 313-327), Berlin Heidelberg: Springer.

Ricci, F., Rokach, L., & Shapira, B. (2011).*Introduction to recommender systems handbook* (pp. 1-35). Springer US.

Robinson, V. 2007. *School Leadership and Student Outcomes: Identifying What Works and Why*. Winmalee, NSW: Australian Council of Leaders. [online] Retrieved from http://tinyurl.com/mhj2um6

Romero-Zaldivar, V. A., Pardo, A., Burgos, D., & Kloos, C. D. (2012). Monitoring student progress using virtual appliances: A case study. *Computers & Education, 58*(4), 1058-1067.

Rowe, C. (1995). Clarifying the use of competence and competency models in recruitment, assessment and staff development. *Industrial and Commercial Training. 27(*11*)*, 12 – 17

Sampson, D., & Fytros, D. (2008). Competence models in technology-enhanced competence-based learning. In H. Adelsberger, Kinshuk, J. Pawlowski (Eds.) *Handbook on Information Technologies for Education and Training* (pp. 155-177). Springer Berlin Heidelberg

Sampson, D. G., Zervas, P., & Sotiriou, S. (2011). Learning object repositories for science education: the case of the OpenScienceResources repository. In *Advanced Learning Technologies (ICALT), 2011 11th IEEE International Conference on* (pp. 358-359). IEEE.

Sanchez, R. (2004). Understanding competence-based management: Identifying and managing five modes of competence. *Journal of Business Research, 57(*5*)*, 518-532.

Sang, G., Valcke, M., van Braak, J., & Tondeur, J. (2010). Student teachers' thinking processes and ICT integration: Predictors of prospective teaching behaviors with educational technology. *Computers & Education, 54*(1), 103-112.

Santos, J. L., Verbert, K., Govaerts, S., & Duval, E. (2013). Addressing learner issues with StepUp!: An evaluation. In *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (pp. 14-22). Leuven: ACM.

Saphier, J., & King, M. (1985). Good seeds grow in strong cultures. *Educational Leadership, 42(6)*, 67-74.

Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2001). Item-based collaborative filtering recommendation algorithms. In *Proceedings of the 10th international conference on World Wide Web*(pp. 285-295). ACM.

Schafer, J. B., Frankowski, D., Herlocker, J., & Sen, S. (2007). Collaborative filtering recommender systems. In *The adaptive web* (pp. 291-324). Springer Berlin Heidelberg.

Schechter, C., & Atarchi, L. (2014). The Meaning and Measure of Organizational Learning Mechanisms in Secondary Schools. *Educational Administration Quarterly*, *50*(4), 577-609.

Scheuer, O., & Zinn, K. (2007) How did the e-learning session go? - The student inspector. *Artificial Intelligence in Education, 158*, 487-494.

Schiaffino, S., & Amandi, A. (2009). Intelligent user profiling. In M. Bramer (Eds) *Artificial Intelligence An International Perspective* (pp. 193-216). Springer Berlin Heidelberg.

Schirru, R., Baumann, S., Memmel, M., & Dengel, A. (2010). Extraction of Contextualized User Interest Profiles in Social Sharing Platforms. *J. UCS*, *16*(16), 2196-2213.

Schildkamp, K., & Ehren, M. (2013). From "Intuition"- to "Data"-based Decision Making in Dutch Secondary Schools?. In K. Schildkamp, M.K. Lai, L. Earl (Eds.). *Data-based Decision Making in Education* (pp. 49-67), Dordrecht: Springer.

Schildkamp, K., Karbautzki, L., & Vanhoof, J. (2014). Exploring data use practices around Europe: Identifying enablers and barriers. *Studies in educational evaluation, 42*, 15-24.

Schildkamp, K., & Kuiper, W. (2010). Data-informed curriculum reform: Which data, what purposes, and promoting and hindering factors. *Teaching and Teacher Education, 26*(3), 482-496

Schneider, M., & Somers, M. (2006). Organizations as complex adaptive systems: Implications of complexity theory for leadership research. *The Leadership Quarterly, 17*(4), 351-365.

Schleicher, A. (2015). *Schools for 21st-Century Learners: Strong Leaders, Confident Teachers, Innovative Approaches.* OECD Publishing

Schoefegger, K., Seitlinger, P., & Ley, T. (2010). Towards a user model for personalized recommendations in work-integrated learning: A report on an experimental study with a collaborative tagging system. *Procedia Computer Science*, *1*(2), 2829-2838.

Schoen, L. T., & Teddlie, C. (2008). A new model of school culture: a response to a call for conceptual clarity. *School Effectiveness and School Improvement, 19(*2*)*, 129-153.

Sergis, S., Zervas, P., & Sampson, D.G. (2014a). A Holistic Approach for Managing School ICT Competence Profiles towards Supporting School ICT Uptake. *International Journal of Digital Literacy and Digital Competence, 5*(4), 34-47.

Sergis, S., Sholla, I., Zervas, P., & Sampson, D.G. (2014b). Supporting school ICT uptake: The ASK School ICT Competence Management System. In *International Conference on Interactive Mobile Communication Technologies and Learning (IMCL2014),* pp. 359-363.

Sergis, S., Zervas, P., & Sampson, D.G. (2014c). ICT competence-based learning object recommendations for teachers. In *Proceedings of the 1th International Conference on Cognition and Exploratory Learning in Digital Age* (pp. 150-157). Porto: IADIS

Sergis, S., Zervas, P., & Sampson, D. G. (2014d). Towards learning object recommendations based on teachers' ICT competence profiles. In *Proceedings of the IEEE 14th International Conference on Advanced Learning Technologies* (pp. 534-538). Athens: IEEE

Sergis, S. & Sampson, D. G. (2014a). From teachers' to schools' ICT competence profiles. In D. G. Sampson, D. Ifenthaler, J. M. Spector & P. Isaias (Eds.), *Digital Systems for Open Access to Formal and Informal Learning* (pp. 307-327). International Publishing: Springer.

Sergis, S., & Sampson, D. G. (2014b). Eliciting teachers' ICT competence profiles based on usage patterns within learning object repositories. In Proceedings of the *Sixth IEEE International Conference on Technology for Education* (pp. 99-105). Amrita: IEEE

Sergis, S., & Sampson, D. G. (2016a). Data driven decision making for school leadership: A critical analysis of supporting systems. In R. Huang, Kinshuk, & J. K. Price (Eds.), *ICT in Education in Global Context: Comparative Reports of K-12 Schools Innovation*.

Sergis, S., & Sampson, D. G. (2016b). Learning object recommendations for teachers based on elicited ICT competence profiles. *IEEE Transactions on Learning Technologies* (*ahead-of-print*).

Sergis, S., & Sampson, D. G. (2016c). Towards a teaching analytics tool for supporting reflective educational (re)design in inquiry-based STEM education. In *Proceedings of the IEEE 16th International Conference on Advanced Learning Technologies* (In Press). Austin, Texas: IEEE

Sergis, S., & Sampson, D.G. (2016d). School Analytics: A Framework for Supporting Systemic School Leadership. In J. M. Spector, D. Ifenthaler, D. Sampson, & P. Isaias (Eds.), *Competencies in Teaching, Learning and Educational Leadership in the Digital Age* (pp. 79-122), International publishing: Springer

Sergis, S., & Sampson, D.G. (2017). Teaching and Learning Analytics to support Teacher Inquiry: A Systematic Literature Review. In P. Pena-Ayala (Ed) Learning analytics: Fundaments, applications, and trends: A view of the current state of the art. Springer

Sergis, S., Zervas, P., & Sampson, D. G. (2014a). Towards learning object recommendations based on teachers' ict competence profiles. In *Proceedings of the IEEE 14th International Conference on Advanced Learning Technologies* (pp. 534-538). Athens: IEEE.

Sergis, S., Sampson, D., Pelliccione, L., Rodriguez, M., Gillet, D. & de Jong, T. (2017a). A Teaching and Learning Analytics Tool for Reflective Educational (re)Design in Inquiry-based STEM Education. *Computers in Human Behavior*, Elsevier

Sergis, S., Sampson, D., & Giannakos, M. (2017b). Enhancing student digital skills: Adopting an ecosystemic School Analytics approach. In *17th IEEE International Conference on Advanced Learning Technologies*

Shani, G., & Gunawardana, A. (2011). Evaluating recommendation systems. In F. Ricci, L. Rokach, B. Shapira, & P. B. Kantor (Eds.), *Recommender systems handbook* (pp. 257-297). NY:Springer.

Shelton, B. E., Duffin, J., Wang, Y., & Ball, J. (2010). Linking open course wares and open education resources: creating an effective search and recommendation system. *Procedia Computer Science*, *1*(2), 2865-2870.

Sielis, G. A., Mettouris, C., Tzanavari, A., & Papadopoulos, G. A. (2011). Context-aware recommendations using topic maps technology for the enhancement of the creativity process. *Educational Recommender Systems and Technologies: Practices and Challenges*, 43-66.

Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist, 57*(10), 1380–1400.

Siemens, G., & Baker, R. S. (2012). Learning analytics and educational data mining: towards communication and collaboration. In *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 252-254). Vancouver: ACM.

Siemens, G., Gašević, D., Haythornthwaite, C., Dawson, S. Shum, S. B., Ferguson, R. et al. (2011). Open learning analytics: An integrated & modularized platform, proposal to design, implement and evaluate an open platform to integrate heterogeneous learning analytics techniques. society for learning analytics research. Retrieved from http://solaresearch.org/OpenLearningAnalytics.pdf.

Smith, V. C., Lange, A. & Huston, D. R. (2012). Predictive modeling to forecast student outcomes and drive effective interventions in online community college courses. *Journal of Asynchronous Learning Networks, 16*(3), 51-61.

Snyder, K. J. (1988). *School Work Culture Profile*. Tampa, FL: School Management Institute.

Snyder, S. (2013). *The simple, the complicated, and the complex: Educational reform through the lens of complexity theory*. OECD Education Working Papers, 96, OECD Publishing.

Society for Learning Analytics Research (SOLAR) (2011). 1st International Conference on Learning Analytics and Knowledge 2011

Solar, M., Sabattin, J., & Parada, V. (2013). A Maturity Model for Assessing the Use of ICT in School Education. *Educational Technology & Society, 16*(1), 206-218

Somekh, B. (2008). Factors affecting teachers' pedagogical adoption of ICT. In *International handbook of information technology in primary and secondary education* (pp. 449-460). Springer US.

Spanos, Y. E., & Prastacos, G. (2004). Understanding organizational capabilities: towards a conceptual framework. *Journal of Knowledge Management, 8(3)*, 31-43.

Spencer, L. M., & Spencer, S. M. (1993). *Competence at work: Models for superior performance*. New York: John Wiley.

Staessens, K. (1990). *Professional culture of innovating primary schools: empirical research in V.L.O.-schools*. Unpublished PhD Dissertation, Katholieke Universiteit Leuben, Leuven.

Stoof, A., Martens, R. L., Van Merriënboer, J. J. G., & Bastiaens, T. J. (2002). The boundary approach of competence: a constructivist aid for understanding and using the concept of competence. *Human Resource Development review, 1*, 345-365.

Stuart, L. H., Mills, A. M., & Remus, U. (2009). School leaders, ICT competence and championing innovations. *Computers & Education, 53*(3), 733-741.

Stufflebeam, D. L., & Shinkfield, A. J. (2007). *Evaluation theory, models, and applications*. San Francisco, CA: Jossey-Bass

Sultana, R. G. (2009). Competence and competence frameworks in career guidance: complex and contested concepts. *International Journal For Educational And Vocational Guidance, 9(*1*)*, 15-30.

Sun, M., Frank, K. A., Penuel, W. R., & Kim, C. M. (2013). How external institutions penetrate schools through formal and informal leaders. *Educational Administration Quarterly, 49*(4), 610-644.

Taatila, V. (2004). *The concept of organizational competence: a foundational analysis*. PhD dissertation. University of Jyväskylä.

Taylor, L., & McAleese, V. (2012). Beyond retention: Using targeted analytics to improve student success. Retrieved from http://tinyurl.com/dyyoqe2.

Teece, D. J. 2007. Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal, 28(*13*)*, 1319-1350.

TLEC (Teacher Leadership Exploratory Consortium) (2010). *Teacher Leader Model Standards* [online] Retrieved from http://www.teacherleaderstandards.org/downloads/TLS_Brochure.pdf

Tempelaar, D. T., Heck, A., Cuypers, H., van der Kooij, H., & van de Vrie, E. (2013). Formative assessment and learning analytics. In *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (pp. 205-209). Leuven: ACM.

Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015). In search for the most informative data for feedback generation: Learning Analytics in a data-rich context. *Computers in Human Behavior*, *47*, 157-167.

Timperley H., Wilson A., Barrar H et al (2010). *Teacher Professional Learning and Development*. Report for the New Zealand Ministry of Education. http://www.oecd.org/edu/school/48727127.pdf

Tondeur, J., Coopert, M., & Newhouse, C. P. (2010). From ICT coordination to ICT integration: A longitudinal case study. *Journal of Computer Assisted Learning, 26(*4*)*, 296–306

Tripathi, P., & Ranjan, J. (2013). Data flow for competence management and performance assessment systems: educational institution approach. *International Journal of Innovation and Learning, 13*(1), 20–32

Trombly, C.E. (2014). Schools and complexity. *Complicity: An International Journal of Complexity and Education, 11*(1), 40-58.

Tsai, K. H., Chiu, T. K., Lee, M. C., & Wang, T. I. (2006). A learning objects recommendation model based on the preference and ontological approaches. In *Sixth IEEE International Conference on Advanced Learning Technologies (ICALT'06)* (pp. 36-40). IEEE.

Uhl-Bien, M., & Marion, R. (2009). Complexity leadership in bureaucratic forms of organizing: A meso model. *The Leadership Quarterly, 20*(4), 631-650.

Uhl-Bien, M., Marion, R., McKelvey, B. (2007). Complexity leadership theory: Shifting leadership from the industrial age to the knowledge era. *The Leadership Quarterly, 18*(4), 298-318.

Underwood, J., Baguley, T., Banyard, P., Dillon, G., Farrington-Flint, L., Hayes, M., ... & Selwood, I. (2010). Understanding the impact of technology: Learner and school level factors. [online] Retrieved from http://oro.open.ac.uk/34529

UNESCO (2011). *ICT Competency Framework for Teachers*. [online] Retrieved from http://unesdoc.unesco.org/images/0021/002134/213475E.pdf van Barneveld, A., Arnold, K. & Campbell, J. (2012). Analytics in higher education: Establishing a common language. *EDUCAUSE Learning Initiative, 1*, 1-11.

Van der Kleij, F. M., Vermeulen, J. A., Schildkamp, K., & Eggen, T. J. (2015). Integrating data-based decision making, Assessment for Learning and diagnostic testing in formative assessment. *Assessment in Education: Principles, Policy & Practice, 22*(3), 324-343.

Van Leekwijck, W., & Kerre, E. E. (1999). Defuzzification: criteria and classification. *Fuzzy sets and systems*, *108*(2), 159-178.

Vanderlinde, R., Aesaert, K., & Van Braak, J. (2014). Institutionalised ICT use in primary education: A multilevel analysis. *Computers & Education, 72*, 1-10

Verbert, K., Drachsler, H., Manouselis, N., Wolpers, M., Vuorikari, R., & Duval, E. (2011). Dataset-driven research for improving recommender systems for learning. In*Proceedings of the 1st International Conference on Learning Analytics and Knowledge* (pp. 44-53). ACM.

Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist, 27*(10), 1500-1509.

Verbert, K., Manouselis, N., Drachsler, H., & Duval, E. (2012a). Dataset-driven research to support learning and knowledge analytics. *Educational Technology & Society, 15*(3), 133–148.

Verbert, K., Manouselis, N., Ochoa, X., Wolpers, M., Drachsler, H., Bosnic, I., & Duval, E. (2012b). Context-aware recommender systems for learning: A survey and future challenges. *IEEE Transactions on Learning Technologies*, *5*(4), 318-335.

Vialardi, C., Chue, J., Peche, J. P., Alvarado, G., Vinatea, B., Estrella, J., & Ortigosa, Á. (2011). A data mining approach to guide students through the enrollment process based on academic performance. *User Modeling & User-Adapted Interaction, 21*(1-2), 217–248.

Vieluf S., Kaplan, D., Klieme, E., & Bayer, S. (2013). *Teaching Practices and Pedagogical Innovation: Evidence from TALIS*, OECD Publishing. [online] Retrieved from http://tinyurl.com/p78w77w

Volungeviciene, A., Tereseviciene, M., & Tait, A.W. (2014). Framework of quality assurance of TEL integration into an educational organization. *The International Review of Research in Open and Distributed Learning, 15*(6).

Walker, A., Recker, M. M., Lawless, K., & Wiley, D. (2004). Collaborative information filtering: A review and an educational application. *International Journal of Artificial Intelligence in Education*, *14*(1), 3-28.

Wallace Foundation (2013). *The School Principal As Leader: Guiding Schools To Better Teaching And Learning*. [online] Retrieved from http://tinyurl.com/azcy2ww

Wallis, S. E. (2008). Emerging order in CAS theory: Mapping some perspectives. *Kybernetes, 37*(7), 1016-1029.

Wang, Y., & Sumiya, K. (2010). Semantic ranking of lecture slides based on conceptual relationship and presentational structure. *Procedia Computer Science*, *1*(2), 2801-2810.

Wasson, B., Hanson, C., & Mor, Y. (2016). Grand Challenge Problem 11: Empowering Teachers with Student Data. In J. Eberle, K. Lund, P. Tchounikine, & F. Fischer (Eds.), *Grand Challenge Problems in Technology-Enhanced Learning II: MOOCs and Beyond* (pp. 55-58), International Publishing, Springer

Wesselink, R., & Wals, A. (2011). Developing competence profiles for educators in environmental Education organisations in the Netherlands. *Environmental Education Research, 17(*1*)*, 69-90.

West, D.L., Peck, C.M., Reitzug, U.C., & Crane E.A. (2014). Accountability, autonomy and stress: principal responses to superintendent change in a large US urban school district. *School Leadership & Management, 34*(4), 372-391.

Winterton, J. (2009). Competence across Europe: highest common factor or lowest common denominator?. *Journal of European Industrial Training, 33(*8,9*)*, 681 – 700.

Woosley, S., & Jones, D. (2011). The foundations of MAP-works. Retrieved from http://tinyurl.com/q2t833f.

Xing, W., Guo, R., Petakovic, E., & Goggins, S. (2015). Participation-based student final performance prediction model through interpretable Genetic Programming: Integrating learning analytics, educational data mining and theory. *Computers in Human Behavior*, *47*, 168-181.

Yukl, G. A. 2002. *Leadership in Organizations* (5th ed). Upper Saddle River, NJ: Prentice-Hall.

You, J.W. (2016). Identifying significant indicators using LMS data to predict course achievement in online learning. *The Internet and Higher Education*,*29*, 23-30.

Zacharis, N. Z. (2015). A multivariate approach to predicting student outcomes in web-enabled blended learning courses. *The Internet and Higher Education*, *27*, 44-53.

Zaldivar, V. A. R., & Burgos, D. (2010). Meta-Mender: A meta-rule based recommendation system for educational applications. *Procedia Computer Science*, *1*(2), 2877-2882.

Zangiski, M. A. D. S., de Lima, E. P., & da Costa, S. E. G. (2013). Organizational competence building and development: Contributions to operations management. *International Journal of Production Economics*, *144(*1*),*76-89.

Zanker, M., & Jessenitschnig, M. (2009). Case-studies on exploiting explicit customer requirements in recommender systems. *User Modeling and User-Adapted Interaction*, *19*(1-2), 133-166.

Zapata, A., Menéndez, V. H., Prieto, M. E., & Romero, C. (2013). A framework for recommendation in learning object repositories: An example of application in civil engineering. *Advances in Engineering Software, 56*, 1-14.

Zhang, H., Almeroth, K., Knight, A., Bulger, M., & Mayer, R. (2007). MOODOG: Tracking students' online learning activities. In *World Conference on Educational Multimedia, Hypermedia and Telecommunications* (pp. 4415-4422). Vancouver: AACE.

Zervas, P., Chatzistavrianos, K., & Sampson, D. G. (2014). Towards Modelling Teachers' ICT Competence Profile in Europe. In R. Huang, Kinshuk, & J.K. Price (Eds). *ICT in Education in Global Context* (pp. 163-181). Springer Berlin Heidelberg.

Zhao, Y., & Frank, K. A. (2003). Factors affecting technology uses in schools: An ecological perspective. *American educational research journal*, *40*(4), 807-840

Zhu, C., Devos, G., & Li, Y. (2011). Teacher perceptions of school culture and their organizational commitment and well-being in a Chinese school. *Asia Pacific Education Review, 12(*2*)*, 319-328.

Short CV

Stylianos E. Sergis has received a Bachelor in Informatics and Telecommunications from the National and Kapodistrian University of Athens, Greece in 2010 and a Master's Degree in ICT in Education from the Faculty of Primary Education of the National and Kapodistrian University of Athens, Greece in 2012.

Stylianos is the co-author of 30 scientific publications and he has received a Best Full Paper Award in the 16th IEEE International Conference on Advanced Learning Technologies (ICALT 2016), Austin, Texas, USA, July 2016.

Stylianos is also a member of the Executive Board of the *IEEE Technical Committee on Learning Technology* and the Editorial Assistant of the *Educational Technology and Society Journal*. He is also an IEEE student member.