PERFORMANCE & EMOTION – A STUDY ON ADAPTIVE E-LEARNING BASED ON VISUAL/VERBAL LEARNING STYLES [1]

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ABSTRACT

Adaptive eLearning systems are able to adjust to a user's learning needs, usually by user modeling or tracking progress. Such learner-adaptive behavior has rapidly become a hot topic for eLearning, furthered in part by the recent rapid increase in the use of MOOCs (Massive Open Online Courses). A lack of general, individual, and situational data about student populations currently hampers the infusion of effective adaptive behavior into existing eLearning platforms. This contribution presents original research on using differences in individual learning styles. Factors related to performance, motivation, satisfaction, and previous knowledge were targeted and used to assess the effectiveness of the approach. We discuss alternative bases for adaptation (e.g. cognitive styles), style distributions in student populations, and conclude with repercussions for adaptive behavior in HCI in general.

KEYWORDS

Adaptive eLearning, Learning Styles, eLearning, Inter-individual Differences, Learner Satisfaction, Motivation

1. INTRODUCTION

Recently, MOOCs have seen a rapid increase in use, both in the number of courses that are on offer, often for free, as well as in attendance per course, with participant numbers surpassing 230,000 for individual courses (Jordan 2014). Additionally, students are drawn from increasingly heterogeneous population groups (e.g., regarding age or cultural and educational backgrounds) (Ha 2014). There is every indication that such development will be continuing for the coming years, as additional universities, companies, educational alliances, and funding agencies are increasing their commitments, and as MOOCs (along with eLearning systems in general) are frequently seen as a suitable instrument to further social inclusion on national and international levels. Last, the continuing increase in the use of mobile devices can be expected to additionally increase the use of eLearning, as learning can spread to more diverse settings, contexts, and locations outside the traditional classroom. This creates new challenges for human-computer interaction in eLearning systems.

Compared to traditional, classroom-based learning, eLearning is characterized, among other differences, by a dramatically decreased instructor/student ratio (with less time and less other resources available per student) and a dramatically increased variation in the student population and in contexts and patterns of use. In brief, there exists less option for the instructor to adapt and mediate a course's content to the individual student, and more need to do so. This is a gap that eLearning systems need to increasingly fill. In the fields of CSCW and Ubiquitous Computing, there has been a significant amount of research on systems that leverage communication or exchange between learners and instructors, or among learners, aiming to bridge this gap (e.g. Abowd et al. 1999, Di Cerbo et al. 2010). In such systems, chats, message boards, or shared documents

[1] Excerpts of this paper have already been presented as a short article (poster) at the Human Computer Interaction Conference, Munich, in September 2014.

help to create social awareness and ease getting in touch with fellow learners. Other contributions pointed to beneficial effects of guidance or framing in facilitating collaboration among learners in MOOCs (Kizilcec 2013). While such approaches certainly represent important contributions to effective eLearning in general, we believe that a promising approach to filling the gap lies in tailoring or mediating the standard content of online courses such that it will adequately fit and adapt to students' individual backgrounds and learning styles. The goal is to maintain efficiency and effectiveness of the individual learning experience.

Adaptivity seems of specific importance for eLearning, due to learners' differences in goals, learning styles, previous knowledge, and backgrounds, and because eLearning systems permit creating individual learning paths (Brusilovsky 1996). Adaptive eLearning systems should be able to respond to individual variables and provide a personal access to learning material (e.g. by adapting it to individual needs). This contrasts with the current state of eLearning systems, in which material is largely available in the same format for all learners (Hauger & Köck 2007).

A number of important learner variables to which a system can adapt address cognitive factors. Mayer and Massa (2003) differentiate between cognitive abilities (i.e. what people are capable of doing), cognitive styles (i.e. ways in which people process and represent information), and learning preferences (i.e. ways in which people like information to be presented to them). We will employ this categorization, while referring to Mayer and Massa's learning preferences as learning styles. One should take note that the terms cognitive and learning styles are not used consistently in the literature, nor are they always precisely defined (Riding & Cheema 1991). Riding and Cheema describe learning styles as a type of cognitive style for a learning situation. Hartley (1998) considers learning styles as the learner's individual way to solving a learning exercise. The terms are used in educational psychology to describe inter-individual differences in learning contexts (Dung & Florea 2012). Such inter-individual differences in abilities and styles correspond to the tier of individual factors described by Bertel (2010) in a tiered factor user model for joint human-computer reasoning tasks.

This paper presents original research on whether an adaptation of eLearning material to inter-individual differences in learning styles can increase learning effectiveness and efficiency, learner motivation, and learner satisfaction. We will present a behavioral study and analyze and discuss resulting data, also with regard to alternative bases for adaptation, such as cognitive styles, and to properties of distributions of styles and preferences in relevant student populations. The paper will conclude with a discussion of possible repercussions for adaptive behavior in human-computer interaction in general and of future work.

2. METHODOLOGY AND METHOD

For modeling learning styles on an individual basis, we chose to employ the *Felder-Silverman Learning Style Model* (*FSLSM;* Felder & Silverman 1988), which, though originally introduced as a model for engineering classes, has been suggested to be well suited for use with eLearning (Carver et al. 1999; Kuljis & Liu 2005). Internal reliability of the *FSLSM* has been validated and tested in various studies (Felder & Spurlin 2005), and the model is based on well-established learning styles, including the *Myers-Briggs Type Indicator* (Briggs Myers & Briggs 1962) and the *Learning Style Inventory* by Kolb (1984) (Felder & Silverman 1988). The *FSLSM*'s four dimensions of altogether eight paired styles are *sequential/global*, *sensing/intuitive*, *active/reflective* and *visual/verbal*. To identify an individual's learning styles, the self-reported *Index of Learning Styles* (*ILS*) questionnaire can be used (Felder & Soloman n. d.). It contains eleven questions for each dimension of the model. For the eight learning styles, it each distinguishes between *balanced*, *moderate*, and *strong* style expressions (cf. Figure 1). An individual learner's expressions on each of these styles are not to be seen as preferences fixed for life, but as variable ones, depending on the learning context.

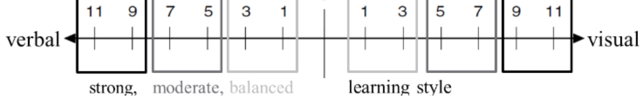

Figure 1. Visual/verbal dimension of the FSLSM and their possible values (based on Felder & Soloman n. d.).

The *visual/verbal* dimension of the *FSLSM* addresses how effectively external information can be processed through which sensory and cognitive modal channels. A predominantly visual learner remembers best what she sees as pictures, diagrams, films, etc. or when she creates a visual mental image based on external information. A predominantly verbal learner prefers words in written or spoken form to learn. For instance, on the *visual/verbal* dimension, balanced learners are able to cope with both representation formats, whereas strong visual learners will likely have problems to learn with verbal representations, and vice-versa.

Within the study reported here, we chose to focus on adapting eLearning material along the *visual/verbal* style pair of the *FSLSM*, in part because the dimension well-investigated, also in cognitive style research, and because a necessary adaptation of the presentation format of our learning material (in order to match with either a visual or verbal learning style, e.g. as pictures or text) could be achieved with limited resources. It has been argued elsewhere that *ILS* results can be used for creating user models in eLearning systems (Paredes & Rodríguez 2002), and the instrument has in fact been employed for several studies of adaptive learning environments (Dung & Florea 2012). Parvez and Blank (2007) argue that the *FSLSM* dimensions and their characteristics are simple enough so that an integration of *ILS* results into eLearning systems becomes feasible. Different learning objects, such as text, images, summaries, exercises etc., can be developed for each dimension and style of the *FSLSM*.

The present study employed our own translation of the *ILS* into German. Internal consistency of the translated version was good, as Cronbach's α for the translated version and for items of the *visual/verbal* scale was .66. This fits coefficients reported by other studies (e.g. Litzinger et al. 2007); it indicates sufficient reliability of the translated instrument (≥0.5 for attitude test, Tuckman and Harper 2012). Additionally, we measured students' individual cognitive styles via a translated version of the *Revised VVQ* by Kirby et al. (1988). This is an adapted version of Richardson's original *Verbaliser-Visualiser Questionnaire* (*VVQ*, Richardson 1977), which, according to Jonassen and Grabowski (1993), is the most frequently used tool to measure visual or verbal ways of thinking. Reliability coefficients for this measure for the *verbal/visual* scales in our study were α=.59 and α=.58, respectively. Though we could trace no other measurements of reliability for the *Revised VVQ* to compare our scores (other than those provided by Kirby et al.) many previous studies have employed the instrument (e.g. Choi & Sardar 2011).

We deem learner's motivation to be essential for learning outcome and believe high motivation levels to be an important precondition for sustained engagement in learning. Learning motivation can be labeled as intrinsic or extrinsic. Pure interests and curiosity have been described to persuade students to learn in a focused manner, requiring little external interventions for sustained learning, as learning is done mostly for its own sake (Brandstätter et al. 2012). In this study, we determined participants' intrinsic motivation based on a self-reported questionnaire by Isen and Reeve (2005). To determine satisfaction with the learning material, we designed a self-reported questionnaire.

Few previous studies have employed the *visual/verbal* learning style of the *FSLSM* in the context of adaptive eLearning (e.g. Brown et al. 2006). While these usually focused solely on measuring performance-related outcomes, we chose to take matters a step further for this study and also focused on emotional factors related to learner satisfaction and motivation. One can argue that, as learners are more on their own during eLearning than during traditional learning formats, there exists more need for sustained high learner motivation. Self-regulated learning is often a challenge for many learners. Intrinsic motivation and high satisfaction levels with the material are thus especially important. Our main research questions were as follows: (Q1) Is there a positive influence of a good fit between the representation format of the learning material and the learning style on learning performance? (i.e., do learning times decrease for constant performance levels? Does performance increase with constant learning times?) (Q2) Does a good fit increase learner motivation and satisfaction?

To answer these questions, we designed a study based on the *Moodle* eLearning platform. 53 participants (26 female, 27 male), with a mean age of 25.3 years [20-34 years], participated voluntarily. There was no reward in terms of money or credits. The study was conducted under laboratory conditions at Bauhaus-Universität Weimar to control and minimize effects of distraction and disruption on the study and on learners' concentration. Participants were either students, mostly of *Computer Science and Media* degree programs, or university staff. They learned at computers and were told that they would be given a quiz about the learning material. Participants were also provided with a questionnaire on their learning motivation and satisfaction. The learning material was taken from an established eLearning course intended for future civil engineers on the theory of oscillations, specifically from a section on the "Basics of Sound". The chosen chapters were comprehensible with secondary school knowledge, and no further instruction in physics or math subjects was required. The material was reproduced in two versions for the learning styles of the *visual/verbal* dimension: one centered mostly on using illustrative diagrams, the other on using textual descriptions. The lecturer of the original course acted as an expert evaluator and ensured that both versions contained the same information and that expected learning times were each at 20 minutes.

The study was of mixed design. As the between-subject component, two groups (A & B) were formed, which received the same learning units, however in different display formats (*visual* or *verbal*). We used *Moodle* to assign a participant to a group based on her individual learning style, as established via the *ILS* instrument. One half of all units were presented according to the individual learning style, the other half were presented in the opposite format. The within-subject component contained the questions of the quiz, and all participants were given the same set of questions. Based on the research questions, the independent variable was the display format (or, more precisely, whether the format matched an individual learner's style, or whether it did not). As dependent variables, study time, test performance as well as learner motivation, and satisfaction with the learning material were used. In addition, participants' individual cognitive styles and previous relevant knowledge were established.

3. RESULTS

As it turns out, three quarters of our participants had a visual learning style (in a simple dichotomy of visual and verbal styles). This corresponds with findings of other studies that about 74% of students (*N>2800*) have visual learning styles (for an overview, see Felder & Spurlin 2005). In natural science study programs, a majority of students are visual (either moderate or strong), whereas the combined percentage of balanced and verbal learners is comparably higher in social science programs (again, see Felder & Spurlin 2005).

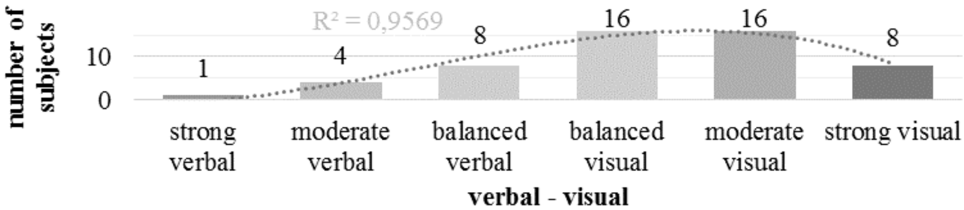

Figure 2. Distribution of the subjects on the learning styles.

A correlation analysis and a set of ANCOVAs showed that previous knowledge had no influence on learning outcomes, nor did it influence motivation, satisfaction, or learning times. Data from one participant was removed before the statistical analysis was conducted because the boxplot of the study time identified it as an extreme value (with more than the triple interquartile range). Another participant did not submit the second part of the quiz; therefore his or her data was not included in the analysis of learning outcomes. As most data was found to be non-normally distributed, we used nonparametric statistical tests (such as Mann-Whitney-U). The two key findings of the study are that (1) there was no significant influence of a good or bad fit between material format and individual learning style on study time and learning outcomes, but that (2) there was a (often, highly) significant influence of a good or bad fit on learner satisfaction and motivation.

The main focus of the further analysis lies on the group of moderate to strong visual learners, as they constituted the largest learning style group of our participants (see Figure 2). We will start by examining performance-related measures (i.e., study times & learning outcomes as measured by performance in the quiz). There were $N=13$ visual style learners in study group A (lesson 1: pictures, lesson 2: text) and $N=10$ visual style learners in group B (lesson 1: text, lesson 2: pictures). We found no significant differences in study times for lesson 1 between groups A ($M=13.63$ *min*) and B ($M=10.52$ *min*) ($U=40.00$, $Z=1{,}550$, *ns*, $r=-.32$), nor for lesson 2 (A: $M=10.10$ *min*, B: $M=9.23$ *min*, $U=56.00$, $Z=-0.558$, *ns*, $r=-.12$). Moreover, we found no significant correlation between the individual cognitive style and study times in matched/mismatched lessons among all subjects ($N=52$). Similarly, a comparison of learning outcomes between groups A and B showed no significant differences for visual learners (lesson 1: A: $M=79.86\%$, B: $M=75.00\%$, $U=43.50$, $Z=-1{,}340$, *ns*, $r=-.28$; lesson 2: A: $M=71.87\%$, B: $M=72.29\%$, $U=64.50$, $Z=-.031$, *ns*, $r=-.01$). There was no significant difference in performance results between lessons that were presented in pictorial and text form. There was also no significant correlation between matched/mismatched individual cognitive styles and learning outcomes for all participants ($N=51$). This confirms findings by Kollöffel (2012) / Brown et al. (2006) who also did not find significant interrelationships between cognitive styles / learning styles and learning outcomes in matched/mismatched courses.

To sum up: There were no significant effects of style match/mismatch on any of the performance-related measures. As we will see in the following, this does, however, not imply that style-to-content matches/mismatches are of no consequence for eLearning and that an adaptation of eLearning content to a learner's individual style would, therefore, be unimportant. Quite the contrary: A comparison of intrinsic motivation levels between groups A and B after lesson 1 (again, for visual learning style participants) showed a significant effect of matching learning style to content format (A, pictures/match: $M=12.54$, B, text/mismatch: $M=8.70$, $U=26.50$, $Z=-2.409$, $p<.05$, $r=-.50$), though no such significant effect could be found for lesson 2 (A, text/mismatch: $M=12.23$, B, pictures/match: $M=10.60$, $U=51.00$, $Z=-0,873$, *ns*, $r=-.18$). Visual participants who received pictorial material in lesson 1 were thus significantly more motivated than visual participants who started with the text material. Interestingly, such high motivation levels did not decline after the second lesson, which was presented as a mismatch (i.e., in text form). In group B, participants started with text; for the visual participants, motivation increased significantly after lesson 2 in which material was presented as pictures. We believe that such dynamics of motivation level due to alternating matches/mismatches merit further research for adaptive eLearning in particular, but also for adaptive human-computer interfaces in general. One interpretation of our data is that high motivation levels caused by style-matched material declines slowly during a mismatch, and that it rises more quickly when mismatched material is followed by matched material.

Data on satisfaction with the learning material was gathered after each lesson, together with the data about learner motivation that we discussed in the preceding paragraph. Again for visual participants, a comparison of satisfaction levels in lesson 1 showed a highly significant difference between group A (pictures/match, $M=9.23$) and B (text/mismatch, $M=6.0$) ($U=23.00$, $Z=-2.654$, $p<.01$, $r=-.55$). This group comparison remained highly significantly different after lesson 2, although with a further increased effect size (A: $M=3.54$, B: $M=10.00$, $U=2.00$, $Z=-4.002$, $p<.001$, $r=-.83$). Even within the groups, we found highly significant effects of a style-matched presentation format on the satisfaction with the material. A Wilcoxon signed-rank test showed highly significant satisfaction differences inside groups A ($Z=-3.066$, $p<.001$, $r=-.85$) and B ($Z=-2.712$, $p<.01$, $r=-.86$). Visual learners were thus highly significantly more pleased with pictorial material. They did not like to learn with text only. Interestingly, none of these tests remain significant when aggregating data from all visual learners (including balanced visual learners). This shows that the effects reported here are really related to an expressed visual learning style, and that learners' individual strengths of style expressions may be just as important for designing effective adaptive behavior in eLearning systems as a sorting into dichotomous *visual/verbal* categories.

A secondary finding of our study is that *ILS* and *Revised VVQ* scores (for learning and cognitive styles, respectively) were highly significantly correlated. To compare the two models, we performed pairwise correlation analyses of the visual/verbal answers of the *ILS* with the corresponding visual/verbal scales of the *Revised VVQ* (visual-to-visual: $r=.84$, $p<.01$, for all our subjects, $N=53$; verbal-to-verbal: $r=.50$, $p<.01$). To our knowledge, a significant correlation between these instruments has not been reported before.

4. CONCLUSION, DISCUSSION AND FUTURE WORK

The aim of this contribution was to see how adaptive behavior can be infused into an existing eLearning platform by categorizing learners into subpopulations according to their individual learning styles, and by then presenting learning material in different matched and mismatched versions for each subpopulation. To this end, we created variants of learning material for an established eLearning course and conducted a behavioral study to investigate effects of matching *visual/verbal* learning styles to corresponding material formats onto learning performance, study times, intrinsic learner motivation, and satisfaction. For the identification of the individual learning style, the *Felder Silverman Learning Style Model* was used, reduced to the *visual/verbal* dimension of the model.

We found no significant influences of a style-matched presentation of learning material on study time and learning outcome. This finding is in line with former research on this topic. However, we equally focused on emotional factors, such as learner motivation and satisfaction. For scores of these factors, a presentation of learning material that is well matched to the individual's style of learning turned out to be highly important.

Emotional factors should not be underestimated for eLearning, as they play a substantial role for self-regulated learning. As Schiefele and Schreyer (1994) demonstrated, intrinsic learning motivation is significantly positively correlated with measures of learning success, such as grades and test results, and high intrinsic motivation encourages in-depth and conceptual forms of learning. In addition, Levy (2007) identified learner satisfaction as a major factor in students' decisions to complete or drop eLearning courses (this is, in fact, a key problem of MOOCs, specifically Jordan 2014). Even though the study on which we reported here did not show a direct influence of style-matched material onto learning success, one could argue that via the discovered strong influence of style-matched learning material on intrinsic motivation, as well as via the influence of intrinsic motivation on learning success widely established elsewhere, an indirect effect of learning style on learning success likely exists. This point clearly requires further and more systematic research.

Further work is also needed to investigate the long-term impacts of style-matched courses on the performance-related factors, either directly or indirectly via emotional factors. We thus suggest to conduct a long-term study and to employ a suitable test-retest procedure that would have to be developed. Moreover, there is a need to conduct such study with a larger sample to verify the results obtained here also for the verbal learners. Ideally such investigation could be conducted in a real learning setting, as extrinsic motivation, such as grades, also play an important, presumptively a negative, role (Lepper et al. 2005).

We argue that some of the findings presented here clearly have important implications for the design of adaptive eLearning courses, as individuals would seem to benefit from style-matched course material. A major factor of relevance of this contribution lies in establishing that a matched visual/verbal learning style is a highly significant factor for the motivation and the satisfaction of the learner. We would also argue that difficulties encountered in the present study by highly unbalanced distributions of learning and cognitive styles in relevant user population of eLearning systems pose challenges not only for developing adaptive eLearning systems, but for developing adaptive human-computer systems in general. When a user is interacting with an adaptive system on a 1-to-1 basis, it is naturally inconsequential for effective adaptive behavior how frequently that user's specific cognitive or other styles (or preferences) are encountered within the relevant user population. What remains important is that the adaptation occurs with respect to specifically those styles (or preferences). For investigating how adaptation should best occur based on a given user type, it is, however, far from being inconsequential how frequently such type is encountered. In the present study, we were largely unable to draw conclusions about users with verbal learning styles, as such users were too rarely encountered within the population of, mostly, STEM[2] students from which we sampled participants. Excluding verbal style learners from using adaptive eLearning systems as a result does not strike us as an attractive conclusion. This problem exists for interaction design in eLearning, as well as for all human-computer interaction types for which inter-individually differing, individual factors of a user will play a role.

We believe that a viable course of action may lie in combining quantitative measures about frequently encountered user types with qualitative measures applied to the more infrequent types. This would have to go hand-in-hand with a graduated approach towards confidence that the adapting system places in its actions, as well with different degrees (i.e., strengths) of adaptation. A second, promising course of action could lie in establishing a tiered user model (along the lines sketched by Bertel 2010), in which the generation of adaptive behavior would resort to being based on general cognitive factors as long as more specific information about a current user and his or her cognitive types or preferences is unavailable.

[2] science, technology, engineering and mathematics

REFERENCES

Abowd, G. D. et al., 1999. Anchoring discussions in lecture: an approach to collaboratively extending classroom digital media. In *Proc. of CSCL'99, C. M. Hoadley and J. Roschelle (Eds.). Intl. Soc. of the Learning Sciences*, Article 1.

Bertel, S., 2010. Supporting joint human-computer reasoning and problem solving: Blueprint of an architecture. In Rapp, D. N. (Ed.): *Proc. of Spatial Cognition 2010 (Posters), SFB/TR 8 report 024-07/2010*, 6.

Brandstätter, V. et al., 2012. *Motivation und Emotion. Allgemeine Psychologie für Bachelor*. Berlin: Springer.

Briggs Myers, I. and Briggs, K., 1962. *The myers-briggs type indicator*: Consulting Psychologists Press.

Brown, E. et al., 2006. Reappraising cognitive styles in adaptive web applications. In: *WWW '06, Proceedings of the 15th international conference on World Wide Web*. New York: ACM, 327–335.

Brusilovsky, P., 1996. Adaptive hypermedia: An attempt to analyze and generalize. In Brusilovsky, P. et al., (Eds.): *Lecture Notes in Computer Science. Multimedia, Hypermedia, and Virtual Reality Models, Systems, and Applications*. Berlin: Springer, pp. 288–304.

Carver, C. et al., 1999. Enhancing student learning through hypermedia courseware and incorporation of student learning styles. *IEEE Transactions on Education*, *42*(1), 33–38.

Choi, J. and Sardar, S., 2011. An Empirical Investigation of the Relationships Among Cognitive Abilities, Cognitive Style, and Learning Preferences in Students Enrolled in Specialized Degree Courses at a Canadian College. *The Canadian Journal for the Scholarship of Teaching and Learning*, *2*(1).

Di Cerbo, F. et al., 2010. Integrating multidimensional means in e-learning. In *Proc. of MTDL '10*. New York: ACM, 31-36.

Dung, P. Q. and Florea, A. M., 2012. An approach for detecting learning styles in learning management systems based on learners' behaviours. In *International Conference on Education and Management Innovation. IPEDR* (30), 171–177.

Felder, R. M. and Silverman, L. K., 1988. Learning and teaching styles in engineering education. *Engineering education*, *78*(7), 674–681.

Felder, R. M. and Soloman, B. A., n. d. *Index of Learning Styles*. Retrieved from http://www.ncsu.edu/felder-public/ILSpage.html

Felder, R. M. and Spurlin, J., 2005. Applications, reliability and validity of the index of learning styles. *International Journal of Engineering Education*, *21*(1), 103–112.

Ha, T.H., 2014. *MOOCs by the numbers: Where are we now?* TED.com. Retrieved from http://blog.ted.com/2014/01/29/moocs-by-the-numbers-where-are-we-now/, updated on 1/29/2014, checked on 3/30/2014.

Hartley, J., 1998. *Learning and studying: A research perspective*. *Psychology focus*. Routledge.

Hauger, D. and Köck, M., 2007. State of the Art of Adaptivity in E-Learning Platforms. *LWA*, 355–360.

Isen, A. M. and Reeve, J., 2005. The Influence of Positive Affect on Intrinsic and Extrinsic Motivation: Facilitating Enjoyment of Play, Responsible Work Behavior, and Self-Control. *Motivation and Emotion*, *29*(4), 295–323.

Jonassen, D. H. and Grabowski, B. L. H., 1993. *Handbook of individual differences, learning, and instruction*. Hillsdale: L. Erlbaum Associates.

Jordan, K., 2014. *MOOC Completion Rates: The Data*. Retrieved from http://www.katyjordan.com/MOOCproject.html

Kizilcec, R. F., 2013. Collaborative learning in geographically distributed and in-person groups. In *AIED 2013 Workshops Proceedings*. Volume 1, pp. 67-74.

Kirby, J. R. et al., 1988. Verbal and visual learning styles. *Contemporary educational psychology*, *13*(2), 169–184.

Kolb, D. A., 1984. *Experimental learning: Experience as the source of learning and development.* Englewood Cliffs: Prentice-Hall.

Kollöffel, B., 2012. Exploring the relation between visualizer–verbalizer cognitive styles and performance with visual or verbal learning material. *Computers & Education*, *58*(2), 697–706.

Kuljis, J. and Liu, F., 2005. A Comparison of Learning Style Theories on the Suitability for elearning. *Web Technologies, Applications, and Services*, 191–197.

Lepper, M. R., et al., 2005. Intrinsic and extrinsic motivational orientations in the classroom: Age differences and academic correlates. *J Educational Psychology*, *97*(2), 184-196.

Levy, Y., 2007. Comparing dropouts and persistence in e-learning courses. *Computers & Education*, *48*(2), 185–204.

Litzinger, T. A. et al., 2007. A psychometric study of the index of learning styles. *Journal of Engineering Education*, *96*(4), 309–319.

Mayer, R. E. and Massa, L. J., 2003. Three Facets of Visual and Verbal Learners: Cognitive Ability, Cognitive Style, and Learning Preference. *Journal of Educational Psychology*, *95*(4), 833–841.

Paredes, P. and Rodríguez, P., 2002. Considering Learning Styles in Adaptive Web-based Education. In *Proceedings of the 6th World Multiconference on Systemics, Cybernetics and Informatics.* Vol. 2, pp. 481–485.

Parvez, S. M. and Blank, G. D., 2007. A pedagogical framework to integrate learning style into intelligent tutoring systems. *Journal of Computing Sciences in Colleges*, *22*(3), 183–189.

Richardson, A., 1977. Verbalizer-visualizer: A cognitive style dimension. *Journal of Mental Imagery*.

Riding, R. and Cheema, I., 1991. Cognitive Styles—an overview and integration. *Educational Psychology*, *11*(3-4), 193–215.

Schiefele, U. and Schreyer, I., 1994. Intrinische Lernmotivation und Lernen: ein Überblick zu Ergebnissen der Forschung. *Zeitschrift für Pädagogische Psychologie*, *8*(1), 1–13.

Tuckman, B. W. and Harper, B. E., 2012. *Conducting educational research* (6th ed). Lanham: Rowman & Littlefield Publishers.