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A Path Model of Effective Technology-Intensive Inquiry-Based Learning

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ABSTRACT

Individual aptitude, attitudes, and behavior in inquiry-based learning (IBL) settings may affect work and learning performance outcomes during activities using different technologies. To encourage multifaceted learning, factors in IBL settings must be statistically significant and effective, and not cognitively or psychomotor intensive. We addressed these questions in a study of 421 students from 11 Slovenian middle schools using an experimental design. Learning achievements were measured by pre- and post-test, while IBL experiences and perceptions were surveyed in a one-shot study. IBL and its effects were successfully measured with a reliable technological literacy test. We designed a path model to capture the effects from multiple interferers. Course content was the most decisive influential factor, with strong impacts on learning achievements, satisfaction, and perceived course intensity. Prior knowledge and capacity, which affects IBL and decreases its psychomotor intensity, was a surprisingly strong influence. IBL had a large, positive effect on technological knowledge and the development of problem solving, critical thinking, and decision-making abilities. The study findings showed that the proposed IBL model is an effective teaching approach in technology-intensive education.

Keywords

Inquiry-based learning, Technology intensive, Technological knowledge and capacity, Students' experiences and satisfaction, Path model

Introduction

Inquiry-based approaches are one of many instructional approaches that use meaningful tasks such as cases, projects, and research to situate learning. Students work in collaborative and cooperative groups to identify what they need to learn to solve a problem, gain research skills, and enhance trade-off capacity (Avsec & Kocijancic, 2014). Inquiry-based learning (IBL) is an inductive learning strategy that enables learners to construct and process knowledge, develop reasoning skills, and to increase interest and learning motivation in technology-intensive learning environments (Hmelo-Silver, Duncan, & Chinn, 2007; Minner, Levy, & Century, 2010; Marshall & Horton, 2011). Alfieri, Brooks, Aldrich and Tenenbaum (2011) stated that "allowing students to interact with materials, models, manipulate variables, explore phenomena, and attempt to apply principles affords them with opportunities to notice patterns, discover their underlying causalities, and learn in ways that are seemingly more robust" (p. 3). The effectiveness of active learning approaches is still a matter of debate at all levels of education (Galand, Frenay, & Raucent, 2012). During recent decades, even in several models of IBL, there has been a lack of reliable quantitative measurement of IBL achievements (Kirschner, Sweller, & Clark, 2006; Marshall, Horton, & Smart, 2009; Alfieri et al., 2011). The quantitative effects in terms of knowledge, problem solving, and developing critical thinking and decision-making (CTDM) capabilities are still lacking. Considering all reported features and influencers, the best IBL environments and models are yet to be discovered. The visualization of factors influencing effective technology-intensive guided IBL in middle school open learning courses is still lacking.

We contribute to the literature by providing evidence of an association between individual IBL acceptance factors (learning environment, material, process, content, reactions, and behavior), individual prior capability, and the performance (knowledge and capacity, satisfaction, and cognitive and psychomotor difficulty) in the context of the middle school inquiry-based open learning environment. Especially, scientists and educators in technology education can benefit from this.

Therefore, the objective of this paper is to investigate what factors in IBL settings encourage multifaceted learning, are statistically significant, satisfying, and effective, and are not cognitive or psychomotor intensive.

Literature review

Research on the impact of IBL on learning is timely because classroom reform discussions are exploring issues of flexible thinking and lifelong learning. Science and technology educators are increasingly interested in IBL as shown by the widespread IBL-related publications. Educators are interested in IBL because of its emphasis on active, transferable learning and its potential for motivating students. By exploiting the capacity of varied technologies, classroom- and/or laboratory-based IBL has become more attainable. Kim and Hannafin (2011) argue that the "evidence of understanding how to support students' IBL in classroom-based, technology-intensive learning environments has been limited, and coherent frameworks to guide implementation have been slow to emerge" (p. 1). Recent efforts by many researchers (e.g., Eisenkraft, 2003; Prince & Felder, 2006; Minner et al., 2010; Marshall & Horton, 2011) showed that IBL was especially attractive to the science community, but the effectiveness of IBL is not yet stable in real-world classrooms using technology-intensive learning environments. Investigations of scaffolding learning in real-world classrooms are scarce (Kim & Hannafin, 2011). IBL has been recommended as a leading instructional strategy for science, but has several limitations in technology-intensive education (Prince & Felder, 2006; Mountrakis & Triantakonstantis, 2012). These limitations are in the instructional materials, learning-process planning used, and the assessment, motivation, and the measurement of metacognitive reflection.

IBL is a learner-centered approach where critical thinking, problem solving, and communication abilities are more important than simply having knowledge about the content of learning (Eisenkraft, 2003; Goldston, Day, Sundberg, & Dantzler, 2010). IBL is a multifaceted activity that uses many methods to collect and analyze data and information, and compares concepts with results to acquire and construct knowledge (Eisenkraft, 2003). IBL requires assumptions to be identified using critical and logical thinking and decision-making with trade-off capacity. IBL may take several forms, including analysis, problem solving, discovery, and creative thinking activities (Saunders-Stewart, Gyles, & Shore, 2012). IBL was developed in response to the perceived failure of more traditional forms of instruction, where students were required simply to memorize fact-laden instructional materials (Hmelo-Silver et al., 2007). IBL is a form of inductive pedagogy, where progress is assessed by how well students develop experimental, analytical, creative, and reflective skills rather than by how many competences they possess (Marshall et al., 2009). Effective IBL implementation is demonstrated through students' performance as formulation of good questions, identification and collection of physical evidence, systematic presentations and elaborations, resolving misconceptions, and management of concept transference (Levy, 2012).

Several types of IBL are discussed in the literature, and they are primarily based on three important qualifiers about the nature of inquiry: the level of scaffolding (amount of learner self-direction), the emphasis of learning, and its scale (within-class, within-course, whole-course, and whole-degree) (Kim & Hannafin, 2011). All IBL models emphasize the following levels of inquiry that differ from one another in significant ways (Minner et al., 2010; Marshall & Horton, 2011; Levy, 2012): (1) confirmation inquiry, (2) structured inquiry, (3) guided inquiry, (4) open inquiry, and (5) blended inquiry. Well-designed IBL environments can enhance students' learning experiences (Goldston et al., 2010; Mountrakis & Triantakonstantis, 2012). IBL tends to improve students' self-regulated learning abilities, but optimal guidance during instruction has to be provided for effective IBL (Kirschner et al., 2006; Goldston et al., 2010; Segedy, Biswas, & Sulcer, 2014). Improvement of transferable skills such as teamwork, independent learning, and problem solving skills in a real-world situation can hopefully improve critical thinking, problem solving, and reduce time pressure in other technology-intensive courses (Segedy et al., 2014). A technology-intensive course engages students in the use of different technologies (production, information, or measurement), and is defined by the following outcomes where students should understand several technology qualifiers and impacts in order to be able to use, judge, assess, and manage different technologies (Garmire & Pearson, 2006; Goldston et al., 2010).

When designing an IBL course, teachers and course designers are faced with several qualifiers of real-world classroom scaffolding learning in order to affect students' experience, knowledge construction and processing, and acquiring skills. Decisions related to the didactic design of a course may refer to one of six fields of IBL:

- Prior knowledge and capacity – Prior knowledge, problem solving, and research skills are crucial for the level of student engagement in IBL. Prior knowledge affects students' process and content knowledge, while prior skills provides better results in metacognitive reflection (Marshall et al., 2009). Prior capacity may reduce perceived course difficulty, and ensure students' course satisfaction (Avsec, Rihtaršič, & Kocijancic, 2014).
- Context – Learners acquire meaning from experience. Therefore, an IBL technology-intensive environment requires multiple resources, access to data, sufficient room for equipment and individual as well as group

activities, discussions, and reflection (Manconi, Aulls, & Shore, 2008; Levy, 2012). The physical learning environment affects learning (Levy, 2012) and satisfaction (Avsec, Rihtaršič, & Kocijancic, 2014).

- Content and learning materials – Active investigations, critical thinking, and reflection provide opportunities for rich interaction with the learning materials. Therefore, students achieve a deep understanding of the content and are better able to apply knowledge and skills (Manconi et al., 2008; Levy, 2012). Multiple forms of learning materials, clear learning objects and objectives, and updated and actual learning materials exploit students' learning styles to enhance higher-order thinking skills (Garmire & Pearson, 2006) and increase students' perceived satisfaction with the course (Avsec, Rihtarsic, & Kocijanic, 2014). The structure and coherence of the curriculum and the learning materials are a major factor for facilitating meaningful learning. The quality of the learning environment and the ease of using an open learning system also contribute to the success and course satisfaction of an IBL course (Prince & Felder, 2006; Avsec, Rihtaršič, & Kocijancic, 2014).
- Process – Activities are guided by students' curiosity and interests, through which they acquire information-processing skills (e.g., critical thinking) that can be generalized across subject domains (Manconi et al., 2008). A well-tailored process allows students to develop self-efficacy where their belief in their own efficacy positively influences their learning achievements and persistence related to specific instructional tasks (Prince & Felder, 2006).
- Strategy of reactions and behavior – Problem solving, planning, organizational, and self-regulation strategies endow students with the skills to perform self-guided and collaborative investigations. Fluid and reflective processes are used instead of linear or cookbook approaches (Manconi et al., 2008; Levy, 2012). Such learning self-regulation is an important characteristic of students' motivation and self-efficacy (Robbins, Lauver, Le, Davis, Langley, & Carlstrom, 2004). Student demographics (age, sex) are considered very important during the planning of course difficulty, especially in randomly chosen samples from different cohorts of students, based on what frequently happens in open learning environments.
- Course Outcomes – Course outcomes may refer to cognitive, emotional, and psychological variables. Learning achievements are considered most important in cognitive variables, which can be described as different facets of competences such as theoretical and methodical knowledge as well as the skills required for problem solving, personal/social competences (e.g., in self-regulated or collaborative learning), and/or technological competence (Garmire & Pearson, 2006; Galand et al., 2012). In emotional variables, student satisfaction with a course is an important outcome that influences the student's decision to continue or drop out of a course (Levy, 2012; Avsec, Rihtaršič, & Kocijancic, 2014). Psychological variable outcomes are based on the perceived difficulty of the course, difficulty of cognitive processing, and the course's psychomotor intensity (Robbins et al., 2004).

New IBL model

Several IBL models circulate in the literature, but three models proved to be effective and were most suitable for this research. Eisenkraft's (2003) 7E model and Marshall, Horton and Smart's (2009) 4E×2 model are most frequently used in science education. The 7E model emphasizes the increasing importance of eliciting prior understandings and the extending or transfer of concepts as transferable competences (Eisenkraft, 2003). Marshall et al.'s (2009) 4E×2 model should be seen as a dynamic IBL model. It allows also formative assessment, use of different inquiry instructional methods, and metacognitive reflection (Marshall et al., 2009). The essential weaknesses (summative assessment and metacognitive reflection) of both models were overcome by a recently developed model by Avsec and Kocijancic (2014). This new model provides summative assessment, active metacognitive reflection, and several feedback mechanisms and assessment through a newly implemented phase of explicit diagnostics and modeling (Figure 1). Metacognitive reflection learning becomes central in all stages of inquiry in this model instead of only in the latter stages of the process. Marshall et al. (2009) argue that when metacognitive reflection and formative assessment are integrated in IBL, teaching becomes more informed and students have more opportunities to monitor their progress in relation to their intended goals.

During the modeling and explicit diagnostics phase, students were engaged in the experiment design and construction to increase the usability of existing experiments. The diagnostics phase combined with the creative-thinking method 635 aimed for multiparametric problem solving and also to boost students' creativity. The course content was enriched with self-made real-world components and models as data sources that were assumed to impact learning achievements (Goldston et al., 2010; Galand et al., 2012), improve the self-regulation process (Marshall et al., 2009), and decrease the physical and cognitive difficulty of the course (Avsec, Rihtaršič, & Kocijancic, 2014).

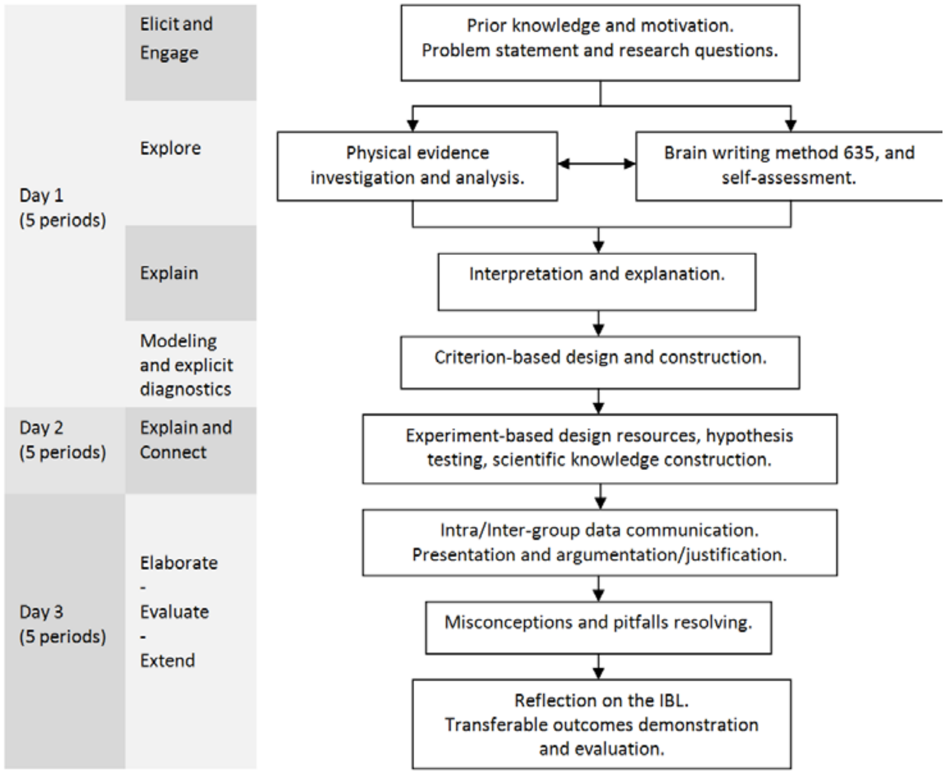

Figure 1. IBL model for technology education

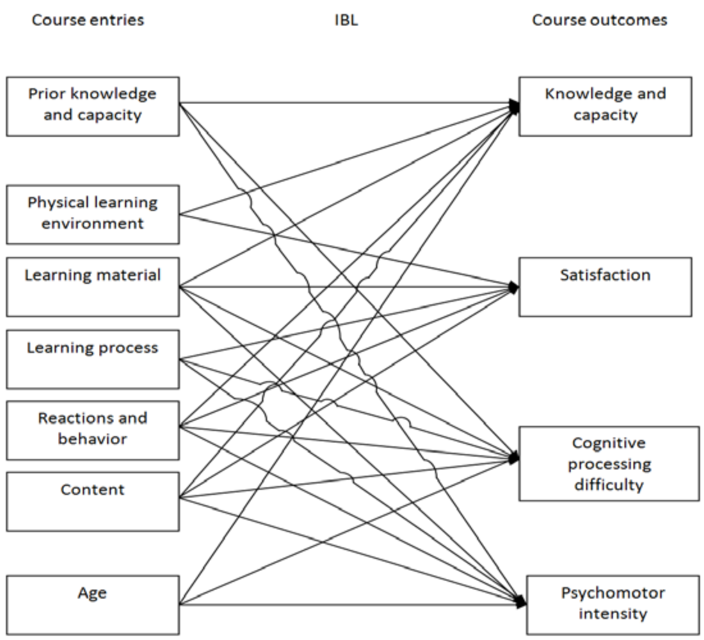

Figure 2. Hypothetical relationships between course entry factors and course outcomes

Research showed that single and linear outcomes and/or effects of IBL in technology-intensive education were investigated, but complex impacts are unknown. The complex interactions of IBL in technology and engineering education may be demonstrated through technological literacy, where the learning effects in technology-intensive open learning have not yet been measured. Briefly, clear empirical evidence on how different fields of guided IBL interact is still lacking. Insights into the interaction of influential factors in IBL could be useful to design effective programs for open learning in science and technology education.

In this study, we empirically investigated the interrelation of different factors of technology-intensive IBL, such as aptitude, attitude, behavior, demographics, learning achievements, satisfaction, and learning difficulty. As Zion and Mendelovici (2012) concluded in their earlier literature review, student aptitude is found to affect learning achievements and, in turn, is supposed to affect students' perceived learning difficulty. Moreover, it is assumed that students' attitude or behavior in IBL positively affects their satisfaction, learning achievements, and learning difficulty (Segedy et al., 2014) while students' demographics (age or sex) could be decisive in IBL achievements and perceived difficulty (Robbins et al., 2004). Hypothesized relations are presented schematically in Figure 2.

Methodology

Research design and the sample

We used an experimental research design to investigate the effectiveness of IBL. This study design used two groups: a control group and treatment group. One group was educated using IBL in an open learning course of technology education consonant with the research recommendations on learning and instruction from a cognitive science perspective (Prince & Felder, 2006). The control group received no IBL in technology and engineering education instruction. Prior knowledge and learning achievements were measured pre- and posttest. Other outcomes such as emotional (satisfaction with the course) and psychological (perceived course difficulty) were surveyed only in the treatment group.

The sample for experimental study was drawn from middle school students. Treatment group students (n_T = 91) were enrolled in an IBL open course of technology education at five middle schools. Control group students (n_C = 338) were not enrolled in IBL at six middle schools. The middle schools recruited in this study were selected by IBL role models (3 university scientists, 3 applied science researchers, 3 young researchers) to assure methodological and IBL requirements. Middle schools recruited in this study had similar demographics (sex or age), a cohort with at least 60–80 students, and social learning skills were needed for the treatment group. IBL was performed from November 2013 to March 2014. The entire course was 3 days long (15 periods). Pre- and post-test surveys were distributed accordingly. The majority (n = 421) of the enrolled students completed the test both times. The participants' sexes were evenly distributed: 50% (n_F = 211) females and 50% (n_{M} = 210) males (1.8% missing values, n = 8). Students were aged 14 ± 1 years. A treatment group were 56 female students (61%) and 35 males (39%).

Instruments

Learning achievements of IBL can be described as different facets of competencies. A holistic method for measurement of technological literacy is proposed for exploring the multifaceted nature of constructs or phenomena (Garmire & Pearson, 2006; Avsec & Kocijancic, 2014). For this purpose, researcher-developed technological literacy multiple-choice test was administered to the students. The test items (TI) were validated by an expert panel. The experts who were selected to serve as content-validation experts were university professors and middle school teaching experts. Evidence of content validity was provided by expert review. Identical versions of the 15-item test were presented at pre- and post-test; the test was subdivided into three subscales based on the subject matter (explicit and implicit) of hydraulic turbines, with five items in each subscale: (1) technological knowledge; (2) problem-solving capabilities; and (3) CTDM abilities. TI examples to measure the achievement of learning objectives in IBL were described elsewhere by Avsec and Kocijancic (2014) while the method for TI construction was described by Avsec and Jamšek (2015).

Student experiences, satisfaction, and perceived course difficulty were considered important for the long-term success of IBL open learning courses. For this purpose, a researcher-developed questionnaire addressing the specifics of the course offerings was administered to the students. The survey items were validated by an expert panel. The expert content validators were university professors and middle school technology teacher experts. An expert panel provided evidence of survey content validity. The survey consisted of five groups of questions with four items, and of three groups of questions with two items in each group. Instrument development was required for the factors affecting the IBL process. For the assessment, a 7-point phrase completion scale was used. The scale intervals form a continuous type from minimum (1) to maximum (7). The scale does not present the mean, but ensures the comparability of continuous responses and produces better assumptions of parametric statistics while avoiding bias (Hodge & Gillespie, 2007).

Data collection

Students participated in the study during real-world classroom sessions throughout a school day. The treatment group students participated in IBL in small groups of 3–4 students (6 groups at the class level) while the control group students had no specific treatment for subject matter except regular traditional lessons. After completion of the pretest, all treatment group students were engaged in 3 days of IBL activities. Administration of the post-test surveys was performed depending on the school curriculum and activity plan, see Table 1.

Table 1. Experimental study phases with dates and instruments used

Middle school	Pilot test		Experimental group			Control group	
	Pre-test	Post-test	Day 1 Pre-test+ IBL	Day 2 IBL	Day 3 IBL+ Post-test + Survey	Pre-test	Post-test
M.K. Ljubljana	12.9.2013	13.11.2013					
K.M. Ljubljana			29.11.2013	23.12.2013	27.1.2014		
Mokronog			4.12.2013	8.1.2014	12.2.2014		
Vrhnika			20.12.2013	24.1.2014	3.3.2014		
Cerklje na Gorenjskem			18.12.2013	29.1.2014	26.2.2014		
Radovljica			10.1.2014	12.2.2014	12.3.2014		
Brestanica						4.2.2014	2.4.2014
Škofja Loka						31.1.2014	3.4.2014
Sežana						15.1.2014	14.3.2014
Črnuče						16.1.2014	19.3.2014
Sostro						20.1.2014	26.3.2014
Kranj						21.1.2014	27.3.2014

Data analysis

Data analysis was conducted using SPSS. In case of the multidimensionality or heterogeneousness of the test, Cronbach's alpha was not suitable as a reliability coefficient (Rossiter, 2010). Therefore, the test–retest reliability was calculated by comparing the scores of 47 students who filled out the test during the first study (September 2013) and again during the second study (November 2013). The intraclass correlation coefficient (ICC) was used as a measure of correlation to contrast with Pearson r correlations (Weir, 2005). To support the criterion-related validity of the test, a corrected Pearson r_{xy} coefficient was used. A corrected Pearson r_{xy} coefficient is an appropriate measure of criterion-related validity (Rossiter, 2010), which served to verify concurrent and predictive validity (Odom & Morrow, 2006). For the purpose of this study, convergent and discriminant validity were assessed by performing an exploratory factor analysis (EFA). However, two criteria were considered to ensure an appropriate sample size was obtained for the current study to enable factor analysis to be undertaken: (a) Kaiser–Meyer–Olkin (KMO) sampling adequacy; and (b) factor loadings and the correlation between a variable and a factor (Stevens, 2009). To demonstrate convergent validity, magnitude of the direct structural relationship between the item and factor should be statistically different from zero (Stevens, 2009). As for discriminant validity, factor correlation matrix analysis has been employed in this study. This method checks the estimated correlations between the factors.

Descriptive analyses were conducted to identify basic information about the students. A two-way analysis of variance (ANOVA) was used to find within-subjects contrasts. We conducted a t-test analysis to find and confirm significant relationships between groups with an effect size calculated with Glass's Δ. We conducted a structural equitation modeling using AMOS software for joint effects of multiple interferers. To uncover the causal relations between the different IBL dimensions, a path model was defined and tested as follows: Outcomes were hypothesized to be influenced by students' prior aptitude, attitude towards learning format, behavior/reactions, and demographics.

Results

Student performance

The reliability of the test was assured by test and retest scores that correlated significantly (Pearson $r_{xy} = 0.877$; $p < 0.01$). The ICC measure (0.93; $p < 0.01$) depicts the strong reliability of the test over time. A high ICC provides a minimum of misclassifications in the measurement of the heterogeneous and complex nature of the construct (Weir, 2005). Correlation analysis of TIs revealed that TIs were negligible ($0.01 < r_{xy} < 0.19$) and weakly correlated ($0.19 < r_{xy} < 0.29$) (Rossiter, 2010) because they were measuring different benchmarks. A low value of the Pearson correlation coefficient ($r_{xy} < 0.29$), demonstrates that all TI were solidly designed and constructed and each TI measures exactly what it was designed for. We provided evidence of high criterion-based validity; therefore, the high concurrent and predictive validity of the results was verified (Odom & Morrow, 2006).

All significance tests for the results were two-tailed. Descriptive statistics for the pre- and post-tests are shown in Table 2. The descriptive data and the comparison of measures of central tendency show that the (14 ± 1)-year-old students taking IBL scored higher on the technological literacy test (mean (M) = 5.03; standard deviation (SD) = 1.85) than those who had no previous IBL exposure (M = 3.22; SD = 1.65). The results indicated a low overall score (maximum of 15), which depicts the high TI difficulty. The test was designed for a 3-year longitudinal study of IBL effects in technology education and it will be exploited in the next 2 years. Further descriptive analysis indicated that the test for homogeneity of variance was nonsignificant, which meant that the sample exhibited characteristics of normality required for analysis under the assumptions of the general linear model. Levene's test for equality of variances achieved no statistical significance at pretest (F (1,419) = 3.03, $p = 0.09 > 0.05$), while the t-test revealed no statically significant differences ($t(419) = –0.57$, $p = 0.57 > 0.05$), and at post-test ($F(1,419) = 3.4$. $p = 0.07 > 0.05$) with t-test ($t(419) = 8.98$, $p = 0.00 < 0.05$).

Table 2. Pre- and post-test descriptive statistics of a treatment and control group (n = 421)

Test	Group	Number of students	*M*	*SD*
Pretest	Treatment	91	3.02	1.56
	Control	330	3.12	1.44
	Total	421	3.09	1.46
Post-test	Treatment	91	5.03	1.85
	Control	330	3.22	1.65
	Total	421	3.61	1.85

A two-way within-subject ANOVA was performed to test how IBL enhances learning in a treatment group. Statistically significant positive impacts were found. IBL statistically significantly effects on learning and skills acquisition ($p < 0.01$) with a positive and large effect size ($\eta^2 = 0.38$). Learning differences were also checked using a t-test where significances were revealed ($F(1,419) = 110.17$, $p = 0.00$) and equal variances were not assumed ($t(99) = 9.24$, $p = 0.00 < 0.05$). Considering unequal sample sizes and variances, we randomly sampled the data of the control group to equalize the samples ($F(1,180) = 41.35$, $p = 0.00$ and $t(119) = 9.42$, $p = 0.00$), while the effect size of Glass's $\Delta = 1.11$ confirms the large effect of IBL. The effect size value should be interpreted cautiously. The small-group learning methods implemented at IBL could increase learning achievement in technology and engineering education with an overall average effect-size of 0.25 (Springer, Stanne, & Donovan, 1999). The different size of the groups at IBL could affect results; the effect size is regarded as small (Springer et al., 1999). The sample size of the two research groups had no influence on the results. No differences were found across the sex distribution ($F(1,419) = 0.64$, $p = 0.42 > 0.05$ and $t(419) = 0.36$, $p = 0.72$).

Student experiences, perceptions, and satisfaction

The findings from literature review revealed subscales for technology-intensive IBL. After revision of the survey, there were four items in each subscale; two items were for overall satisfaction, learning difficulty, and psychomotor intensity as the perceived outcomes of the course. A reliability analysis was performed after administering the survey. The Cronbach's alpha values indicated that the developed instrument was highly reliable for the majority of subscales while it was moderately reliable over time for the subscale of reaction and behavior. We also investigated how students' experiences and perceptions of IBL contribute to course outcomes. Table 3 provides reliability values and descriptive data on subscales for each survey item as expressed in *M* and *SD*. Students expressed the strongest agreement of perceived experiences with the content and learning material ($M = 5.82$, $SD = 1.01$ and $M = 5.82$, $SD = 0.93$, respectively). The component with the lowest ranked perceived experiences was physical learning environment ($M = 5.03$, $SD = 1.28$). IBL difficulty was perceived as semi-intensive on a 7-point interval scale with a midpoint of 4 ($M = 3.66$, $SD = 1.1$). Students needed more room for effective IBL ($M = 4.70$, $SD = 1.47$) while the feedback on IBL and multiple forms of learning material that present a rich data source were ranked high ($M = 6.18$, $SD = 1.02$ and $M = 6.06$, $SD = 1.34$, respectively). Table 3 shows that we can conclude that there is a high level of overall student satisfaction with the course because students felt comfortable with all sections of IBL. The course was well designed and students considered its difficulty to be moderate.

Table 3. Reliability information and descriptives about survey subscales and items ($n = 91$)

Items	Cronbach's alpha	*M*	*SD*
Experiences concerning learning environment (LE)	0.89	5.03	1.28
LE1– Classrooms and laboratories are well equipped and organized		4.80	1.46
LE2– Learning environment is user friendly		5.17	1.64
LE3– Each student has enough room for research and creative work		4.70	1.47
LE4– Refreshment and snacks are available, easy on access		5.50	1.31
Experiences concerning learning material (LM)	0.81	5.82	0.93
LM1– Learning material is up to date and actual		5.57	1.34
LM2– Material gives enough information for inquiry		6.06	1.34
LM3– Learning objectives are clear and well designed		5.94	0.84
LM4– Learning material was of multiple forms and types		5.67	1.07
Experiences concerning learning process (LP)	0.84	5.77	0.93
LP1– Active learning and practical work are enabled		5.93	1.06
LP2– Assistance, self-directed and collaborative work are enabled		5.76	1.21
LP3– I was effective, no need for extra help or teacher guidance		5.59	1.11
LP4– Explanations and instructions were clear and comprehensible		5.81	1.15
Experiences concerning reactions and behavior (RB)	0.68	5.39	0.98
RB1– Learning was effective and success controlled via tests		5.40	1.63
RB2– Learning was creative, own ideas were well considered		5.52	1.40
RB3– Own learning pace was enabled		5.72	1.40
RB4–I can recommend this IBL to fellow students		4.93	0.94
Experiences concerning content (C)	0.86	5.82	1.01
C1– Content is attractive, interesting, suits for males and females		5.67	1.46
C2– Different feedbacks are enabled		6.18	1.02
C3– Language was clear, subject matter content was comprehensible		5.56	1.10
C4– Content was well organized and timely fashion over all IBL days		5.86	1.16
Experiences concerning satisfaction (S)	0.82	5.61	0.84
S1– Overall satisfaction with the IBL teachers		5.56	0.87
S2– Overall satisfaction with the course model		5.66	0.82
Experiences concerning cognitive difficulty (CD)	0.90	3.61	1.17
CD1– I find it difficult to memorize fact-laden materials		3.54	1.14
CD2– I find it difficult to think and to learn new content and concepts		3.68	1.22
Experiences concerning psychomotor intensity (PI)	0.84	3.69	0.97
PI1– I find it difficult to concentrate myself at design activities		3.54	1.01
PI2– I find it difficult to handle with tools and workshop equipment		3.84	0.94

Path model

A path model consists of student performance variables (knowledge, capacity, and CTDM) and variables describing students' perception, experiences and satisfaction. EFA provided evidence of construct validity on the model variables. To ensure an appropriate sample size to undertake factor analysis, the value of KMO sampling adequacy on the survey and test was 0.78 and Bartlett's test of sphericity was significant ($p = 0.00 < 0.05$). The sampling adequacy value of 0.78 for the model variables was very good (Stevens, 2009). On the first-run principal component analysis (PCA), the total variance of the model factors was 71% (seven factors, eigenvalue >1). The communalities h^2 of the all variables on the model were >0.4. The decision to eliminate low-loading variables was confirmed using Steven's (2009) guidelines of statistical significance for interpreting factor loadings. Steven's (2009) guidelines are based on sample size and suggest that the statistically acceptable loading for 91 participants is 0.52. The structure matrix revealed valid variables, which provide evidence of the convergent validity of factors (Table 4). A factor correlation matrix was also calculated where there were very low values of correlations between seven factors and correlations did not exceed 0.36 < 0.7. These factors are distinct and uncorrelated, which shows the high discriminant validity of factors (Stevens, 2009).

Table 4. Structure matrix of variable loadings on the factors performed with PCA

Variable	Component						
	1	2	3	4	5	6	7
Prior knowledge						0.75	
Prior capabilities			–0.84				
Prior CTDM				0.81			
Post CTDM				0.83			
LE1					0.85		
LE2	0.54				0.81		
LE3					0.84		
LE4					0.84		
LM1	0.64						
LM2	0.83						
LM3	0.56	–0.55					
LM4	0.86						
LP1	0.64						
LP2	0.68						–0.52
LP3	0.73						
LP4	0.75						–0.58
RB1							–0.86
RB2	0.53						–0.64
RB3							–0.80
RB4						–0.55	
C1		–0.68					
C2		–0.88					
C3		–0.85					
C4		–0.78					
S1	0.68				0.67		–0.61
S2	0.67				0.59		
CD1		0.82					
CD2		0.73					
PI1			0.90				
PI2			0.84				

Many researchers argue that the most decisive and important variable influencing IBL outcomes might be content (Eisenkraft, 2003; Prince & Felder, 2006; Galand et al., 2012; Levy, 2012). Until now, clear empirical evidence was still lacking. Our research design also provided covariates on students' demographics and we constructed a path model of effective IBL outcomes that are influenced by independent variables. Model fit tests were done in AMOS software, and a path model of IBL dimensions with statistical significant ($p < 0.05$) standardized path coefficients is shown in Figure 3. Exogenous entries in model were sex, age, prior aptitude, learning environment, material and process, reactions and behavior, and content, while endogenous variables were knowledge and capacity, satisfaction, and perceived course difficulty and intensity. All exogenous variables (except sex) effects were hypothesized to be significantly correlated with both positive and negative outcomes.

Figure 3 illustrates the path model after the attenuation correction. IBL outcomes are influenced by variables with significant standardized path coefficients ($p < 0.05$). According to commonly used fit indices (Schermelleh-Engel, Moosbrugger, & Müller, 2003; Blunch, 2013), we found that the fit of this model was very close. A nonsignificant *p*-value (0.57) was observed from the Chi-squared test (16.4), and the Chi square divided by its degrees of freedom was smaller than 5 (0.91). The Goodness of Fit Index, the Comparative Fit Index, and the Tucker–Lewis Coefficient values were larger than 0.95 (0.97, 1.00, and 1.01, respectively), and the root mean-squared error of approximation and the root mean square residual were smaller than 0.05 (0.00 and 0.04, respectively). The probability of close fit was larger than 0.05 (0.77). The probability level of the test of close fit was also higher than the proposed threshold level of 0.50 for a good model fit (Blunch, 2013). This indicates a great initial model that does not need any improvement. All paths in the model showed significant effects.

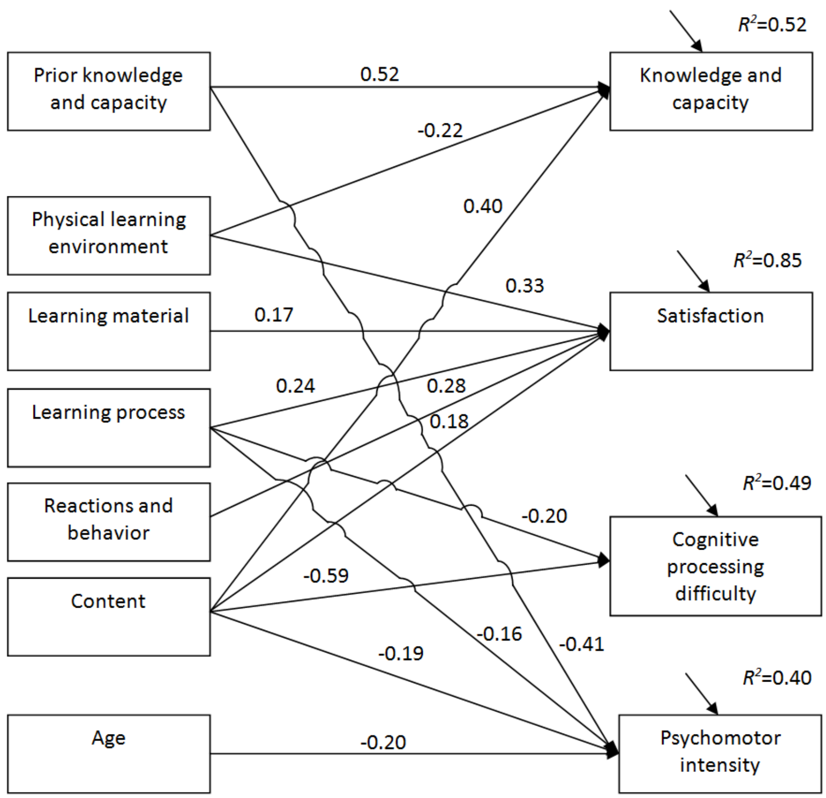

Figure 3. Path model of IBL outcomes and their influencing factors with significant ($p < 0.05$) standardized path coefficients ($n = 91$)

The significant path coefficients varied from medium (0.16) to strong (0.59) and the absolute rate was considered. The variance in IBL learning achievements was explained by influencing variables in 51.6%. The most influential variables were prior knowledge and capacity and IBL content. ANOVA revealed most of the important factors influencing learning achievements. Prior practice and problem-solving skills have the largest positive effect ($p = 0.00$, $\eta^2 = 0.45$). Prior CTDM and clarity of language and subject matter material impacts significantly on learning achievements with a large effect size η^2 (0.24 and 0.23, respectively). In student satisfaction, 85.3% of the variance was explained by learning environment, material, and process, and by the reactions and behavior and content variables in this model. ANOVA revealed that all variables that were correlated with satisfaction have a uniform effect with no statistically differences between each other ($p > 0.05$). The variance of perceived cognitive processing difficulty was explained for 48.6% by learning process and content. ANOVA revealed the most decisive factor with a large effect size, which shows that good organization of the content makes the IBL course easier ($p = 0.01 < 0.05$, $\eta^2 = 0.22$). The high variance in psychomotor intensity was explained for 40.3% by student age, content, learning process, and prior learning practice (knowledge and capacity). The psychomotor intensity might decrease with prior practice (capabilities) and interesting content, which was shown evenly in male and female sexes (p = 0.00, η^2 = 0.53 and p = 0.02, η^2 = 0.23, respectively).

Seven path coefficients had negative estimates. The negative path coefficient for the Learning environment to Learning achievements path orientation means that a highly comfortable learning environment predicts a less-effective IBL. Thereafter, organized, clear, attractive content with enabled feedback mechanisms, and a well-designed learning process decrease the learning difficulty and psychomotor intensity of the course. Prior practice and older students show that the psychomotor intensity of the technology-intensive IBL is easier. The explained variances were calculated using R^2 from path model where R^2 = 0.02 means a small impact, R^2 = 0.13 means a medium effect size, and R^2 = 0.26 presents a large effect size (Cohen, Cohen, West, & Aiken, 2003).

Discussion

The path model of factors influencing course outcomes shows that prior knowledge affects only knowledge acquisition and reduces psychomotor intensity. The physical learning environment improves students' learning and satisfaction, but learning materials influenced only student satisfaction with the course. The learning process influences satisfaction and reduces course difficulty. Students' interactions in scaffolding learning influence satisfaction while content influences all IBL outcomes significantly. The path analysis of factors affecting IBL shows that content is an important influential factor for new knowledge and capacity as well as for the perceived difficulty of the course.

Surprisingly, student age showed low influence; it provided a reduction of course psychomotor intensity. According to previous IBL research, the CTDM component was judged decisive (Manconi et al., 2008, Segedy et al., 2014). Our case revealed a high level of teacher scaffolding and less student involvement. Interactions were not decisive in reducing course difficulty beyond what was expected in open learning systems (Avsec, Rihtaršič, & Kocijancic, 2014). Different feedback mechanisms and prior aptitude were decisive for reducing course difficulty (Segedy et al., 2014) and improving metacognition and higher-order thinking (Marshall & Horton, 2011), which were reflected in increases in knowledge and capacity (Avsec & Kocijancic, 2014). Multiple forms of learning materials seem less decisive in the acquisition of knowledge and skills (Kim & Hannifin, 2011; Levy, 2012) or in perception of difficulty (Hmelo-Silver et al., 2007). CTDM was not developed properly even after several interactions and reflective examination of student's scaffold learning, which again proves that student self-regulation is not a good predictor of course quality. A surprisingly negative and large correlation was found in the learning environment's effects on learning achievements. We can conclude that a well-equipped and comfortable learning environment might decrease the learning achievements for guided self-directed inquiry in technology education.

Conclusion

Only a well-tailored experimental design can produce reliable, valid, and accurate results. The IBL model presented in this study has had positive and large influence on the development of learning achievements. Technology-intensive IBL shows good predisposition in terms of skills and prior knowledge, decreased course intensity (psychomotor and cognitive), and enhanced learning. The path model shows that all path coefficients have a medium to strong effect on course outcomes and should be considered very carefully if we want to make technology-intensive inquiry effective.

In a well-equipped learning environment, a full open inquiry is not recommended for middle school students because it can produce many misconceptions. In that case, we suggest more teacher involvement in guided inquiry or an implementation of structured inquiry. Different feedback mechanisms must be enabled. Our evidence and metrics about effective IBL will contribute significantly to technology educators. Some limitations could consist of the quality of the program, teacher effects, and how the students perform in traditional academic courses. Further research is required to replicate these findings amongst other samples, and to identify whether there are specific variations in IBL practices and styles that are particularly salient to the development of students' problem-solving and CTDM abilities.

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