

**THE DEVELOPMENT AND EVALUATION OF
PERSONALIZED LEARNING MATERIAL
BASED ON A PROFILING ALGORITHM FOR
POLYTECHNIC STUDENTS IN LEARNING
ALGEBRA**

by

NUR AZLINA BINTI MOHAMED MOKMIN

**Thesis submitted in fulfillment of the requirements
for the degree of
Doctor of Philosophy**

JULY 2016

ACKNOWLEDGEMENT

Alhamdulillah, sincere *thanks to the Almighty*, the Creator and the Preserver for giving me the strength and health in this challenging journey. I would like to sincerely express my special thanks to my supervisor, Associate Professor Dr. Mona Masood, who had guided me with patience and wisdom. The encouragement and supervision from her has created a clear path for me to follow from the first step until the end of this long journey. I would like to extend my special thanks to Associate Professor Dr. Zarina Samsudin for giving me guidance and support in improving my writing. I would also like to say thanks to all the lecturers at CITM for their constructive criticism and views related to my study.

My deepest gratitude to the lecturers and friends at Politeknik Tuanku Sultanah Bahiyah and Politeknik Seberang Perai who had been an immense help in this study. Their knowledge, views and support have added valuable input to this study. I would like to acknowledge my appreciation for the administrative staff and students in these polytechnics who had responded to all my requests and requirements related to this study.

Lastly, for my beloved husband Muhammad Afifi Ramli and my mother, Eshah Yahya, thanks for all the unconditional love, understanding, and support in this long journey. For my two boys, Arif Najmi and Amir Naufal, I hope this path that I have gone through will give inspiration for your life ahead.

TABLE OF CONTENTS

ACKNOWLEDGEMENT	ii
TABLE OF CONTENTS	iii
LIST OF TABLES	xi
LIST OF FIGURES	xv
LIST OF EQUATIONS	xviii
LIST OF ABBREVIATIONS	xix
LIST OF SYMBOLS	xx
ABSTRAK	xxi
ABSTRACT	xxiii
CHAPTER ONE - INTRODUCTION	
1.1 Introduction	1
1.2 Background of the Study	5
1.3 Preliminary Study	11
1.4 Problem Statement	13
1.5 Purpose of the Study	14
1.6 Research Objectives	15
1.7 Research Questions	16
1.8 Research Hypotheses	17
1.9 Significance of the Study	18
1.10 Theoretical Framework	20
1.10.1 Case-based Reasoning Algorithm	21
1.10.2 Alessi and Trollip's Instructional Design Model	21
1.10.3 Mathematics Student Learning Style.....	22
1.10.4 Mayer's Cognitive Theory of Multimedia Learning	22

1.10.5	ITS Architecture	22
1.11	Research Framework	23
1.11.1	PLM and NPLM	23
1.11.2	Case-based Similarity Score	23
1.11.3	Algebra Performance	24
1.12	Operational Definitions	24
1.13	Summary	29

CHAPTER TWO - LITERATURE REVIEW

2.1	Introduction	31
2.2	Mathematics	31
2.2.1	Mathematics in Malaysian Polytechnics	32
2.2.2	Sijil Pelajaran Malaysia (SPM) Mathematics	36
2.3	Algebra	36
2.3.1	Algebraic Fractions	39
2.4	Personalization of Mathematics Learning	40
2.5	Prior Knowledge	44
2.6	Learning Style	46
2.7	Mathematics Learning Style	49
2.8	Mastery Learning Style	51
2.8.1	Graduated Difficulty Learning Strategy for MLM	53
2.9	Understanding Learning Style	54
2.9.1	Concept Attainment Learning Strategy for ULM	55
2.10	Self-Expressive Learning Style	56
2.10.1	Inductive Learning Strategy for SLM	57
2.11	Interpersonal Learning Style	58
2.11.1	Real-life Application Learning Strategy for ILM	59
2.12	Intelligent Tutoring System Architecture	60

2.12.1	Domain Model.....	64
2.12.2	Student Model	64
2.12.3	Tutorial Model.....	65
2.12.4	User Interface Model.....	65
2.13	ITS for the Personalization of Mathematics Learning	66
2.13.1	ITS for Algebra Learning	71
2.14	Learning Styles in ITS	74
2.15	Prior Knowledge in ITS	77
2.16	Case-Based Reasoning.....	79
2.16.1	The CBR Cycle.....	81
2.16.2	Case-Based Reasoning Similarity Value.....	84
2.16.3	CBR Applications.....	86
2.17	Alessi and Trollip’s Instructional Design	90
2.17.1	Planning.....	90
2.17.2	Design.....	91
2.17.3	Development.....	91
2.18	Multimedia Learning	92
2.19	Research Gap and Summarization of the Elements	95
2.20	Summary	99

CHAPTER THREE - DESIGN AND DEVELOPMENT

3.1	Introduction.....	100
3.2	Alessi and Trollip’s Instructional Design (ATID) Model.....	100
3.3	Planning Phase	102
3.3.1	Define the Scope	102
3.3.2	Identify learner characteristics	104
3.3.3	Establish the Constraints.....	106
3.3.4	Determine and Collect Resources	106

3.4	Design Phase	107
3.4.1	Develop Initial Content Ideas	108
3.4.2	Conduct Concept Analysis.....	108
3.4.3	Do a Preliminary Program Description.....	109
3.5	Development Phase.....	116
3.5.1	User Interface Model	116
3.5.2	Write the program	116
3.5.3	Create the Graphics.....	117
3.5.4	Produce Audio and Video	122
3.5.6	Assemble the Pieces.....	122
3.6	Cognitive Theory of Multimedia Learning.....	123
3.6.1	Mastery Learning Material (MLM)	124
3.6.2	Understanding Learning Material (ULM)	125
3.6.3	Self-Expressive Learning Material (SLM)	125
3.6.4	Interpersonal Learning Material (ILM)	126
3.7	The Development of Learning Materials	126
3.8	Case-based Reasoning Algorithm.....	127
3.8.1	Retrieve	127
3.8.2	Reuse.....	130
3.8.3	Revise.....	130
3.8.4	Retain	131
3.9	Summary	132

CHAPTER FOUR - METHODOLOGY

4.1	Introduction.....	133
4.2	Population and Sample	133
4.3	Variables	135
4.4	Research Design.....	137

4.5	Research Instrument.....	138
4.5.1	Pretest and Posttest.....	139
4.5.2	Math Learning Style Inventory	140
4.6	Research Permission	140
4.7	Preliminary Study	140
4.7.1	Phase 1: Analysis of the Final Examination Results	141
4.7.2	Phase 2: Survey	142
4.7.3	Phase 3: Interview with the Mathematics Lecturers	142
4.7.4	Phase 4: Algebra Test	143
4.7.5	Math Learning Style Inventory	143
4.8	Pilot Study.....	143
4.8.1	Pretest and Posttest Validity and Reliability.....	145
4.8.2	MLSI Validity and Reliability	147
4.8.3	Data Analysis of the Pilot Study.....	148
4.9	Evaluation of the Instructional Material	150
4.9.1	Alpha Test.....	151
4.9.2	Revision	151
4.9.3	Beta Test	152
4.10	Procedure of the Actual Study	152
4.11	Internal and External Validity.....	154
4.11.1	Internal Validity	154
4.11.2	External Validity	156
4.12	Data Analysis	157
4.13	Summary	157
CHAPTER FIVE - DATA ANALYSIS AND FINDINGS		
5.1	Introduction.....	158
5.2	Distribution of the Sample	158

5.3	The Description of the Statistical Tests and Variables	160
5.4	Hypothesis H_01	162
5.4.1	Assumption of the Mann-Whitney U Test	162
5.4.2	Descriptive Analysis	163
5.4.3	The Results of the Mann-Whitney U Test	164
5.5	Hypothesis H_02	165
5.5.1	Assumptions for ANOVA Test	165
5.5.2	Descriptive Analysis	168
5.5.3	The Results of the ANOVA Test	168
5.6	Hypothesis H_03	169
5.6.1	Assumptions for ANOVA Test	169
5.6.2	Descriptive Analysis	173
5.6.3	The Results of the ANOVA Test	173
5.7	Hypothesis H_04	174
5.7.1	Assumptions for ANOVA Test	174
5.7.2	Descriptive Analysis	177
5.7.3	The Results of the ANOVA Test	177
5.8	Hypothesis H_05	178
5.8.1	Assumptions for ANOVA Test	178
5.8.2	Descriptive Analysis	180
5.8.3	The Results of the ANOVA Test	181
5.9	Hypothesis H_06	181
5.9.1	Assumptions for ANOVA Test	182
5.9.2	Descriptive Analysis	184
5.9.3	The Results of the ANOVA Test	184
5.10	Hypothesis H_07	185
5.10.1	Assumptions for ANOVA Test	185

5.10.2	Descriptive Analysis.....	187
5.10.3	The Results of the ANOVA Test.....	187
5.11	Hypothesis H_08	188
5.11.1	Assumptions for ANOVA Test	188
5.11.2	Descriptive Analysis.....	190
5.11.3	The Results of the ANOVA Test.....	191
5.12	Hypothesis H_09	191
5.12.1	Assumptions for Two-Way ANOVA Test	192
5.12.2	Descriptive Analysis.....	198
5.12.3	The Result of the ANOVA Test	199
5.13	Conclusion of the Data Analysis and Findings for Each Hypothesis	200
5.14	Summary	202
CHAPTER SIX - DISCUSSION, IMPLICATIONS AND RECOMMENDATIONS		
6.1	Introduction.....	203
6.2	The Effect of PLM and NPLM on CSS	204
6.2.1	Case Representation.....	205
6.2.2	The Similarity Value.....	206
6.2.3	The Retrieval Process	207
6.3	The Effect of PLM and NPLM on LGS.....	208
6.3.1	The Effect of PLM for the Learning Materials on LGS	214
6.3.1	The Effect of NPLM for the Learning Materials on LGS	215
6.3.3	The Effect of the Treatments for Each Learning Materials on LGS.....	216
6.3.4	The Interaction between the Learning Materials and the Treatments ..	218
6.4	The Effect of the Learning Materials on the LGS	219
6.4.1	The Effect of the MLM on the LGS	222
6.4.2	The Effect of the ULM on the LGS	225

6.4.3	The Effect of the SLM on the LGS	227
6.4.4	The Effect of the ILM on the LGS	230
6.5	The Limitations of the Study	233
6.6	Implications of the Study	234
6.6.1	The Implications of the Research for Personalization in Learning	234
6.6.2	The Implications for Mathematics Learning	235
6.6.3	The Implication of the Research for ITS	236
6.6.4	The Implications for Polytechnics	237
6.6.5	The Implications for Multimedia Learning	238
6.7	Recommendations for Further Research	238
6.7.1	Recommendations for the Field of Instructional Technology	239
6.7.2	Recommendation for the Field of ITS	240
6.7.3	Recommendations for the Field of Mathematics Education	240
6.8	Summary	241
REFERENCES		243
APPENDICES		265
LIST OF PUBLICATIONS		

LIST OF TABLES

		Page
Table 1.1	Method and Purpose of the Five Phases of Preliminary Study	12
Table 2.1	The PLO for Electrical and Mechanical Engineering Programs	33
Table 2.2	December 2012 DBM 1013 Final Examination Results	35
Table 2.3	June 2013 DBM 1013 Final Examination Results	35
Table 2.4	Personalization of Mathematics Learning	44
Table 2.5	Learning Styles	48
Table 2.6	Mastery Learning Strategies and Description	52
Table 2.7	Understanding Learning Strategies and Description	55
Table 2.8	Self-Expressive Learning Strategies and Description	57
Table 2.9	Interpersonal Learning Strategies and Description	59
Table 2.10	The Developed ITSs for Matematics Learning	69
Table 2.11	ITS for Algebra Learning	73
Table 2.12	ITS that Apply Learning Style Theory	77
Table 2.13	AI Algorithms	80
Table 2.14	ITS that Applied CBR Algorithm	90
Table 2.15	The Elements for this Study	98
Table 3.1	The Learning Outcomes of the Domain Model	104
Table 3.2	The Application Softwares	106
Table 3.3	The Resources	107
Table 3.4	The Eliminated Ideas and Reasons for the Elimination	108
Table 3.5	The Differences between PLM and NPLM	110
Table 3.6	The Principles to Reduce Extraneous Processing	123
Table 3.7	The Principles of Managing Essential Processing	124
Table 3.8	The Principles for Fostering Generative Processing	124

Table 3.9	The Summary of the Design, Strategy and Resource of Reference	126
Table 3.10	Type of Information and the Value Submitted to the Application	129
Table 4.1	Estimation of Total Number of Students by Program	134
Table 4.2	Statistical Design and Reasonable Sample Size	135
Table 4.3	Research Design	138
Table 4.4	Factorial Design (2 x 4) for CBR Similarity Score (CSS)	138
Table 4.5	Factorial Design (2 x 4) for Learning Gain Score (LGS)	138
Table 4.6	The Learning Outcome for Each Question	139
Table 4.7	The Respondents for Preliminary Study	141
Table 4.8	The Pilot Study Objectives	144
Table 4.9	The Pilot Study Arrangement	145
Table 4.10	Cronbach Alpha Reliability Coefficient	147
Table 4.11	The Cronbach Alpha Value and Category for Each Learning Style	148
Table 4.12	The Descriptive Results of CSS for Pilot Study	149
Table 4.13	The Independent T-test Results of CSS for Pilot Study	149
Table 4.14	The Descriptive Result of LGS for Pilot Study	150
Table 4.15	The Independent T-Test Results of LGS for Pilot Study	150
Table 4.16	The Experts' Evaluations	151
Table 4.17	The Students' Evaluations	152
Table 4.18	Distributions of the Student in Actual Study	153
Table 4.19	The Procedures of the Actual Study.	154
Table 4.20	Variables that Affect the Internal Validity	155
Table 4.21	The Threats to External Validity	156
Table 4.22	Statistical Test for Each Hypothesis	157
Table 5.1	Distribution of the Respondents	160
Table 5.2	The Descriptive Analysis for Skewness and Kurtosis for PLM and NPLM	164

Table 5.3	The Ranks of Mean for Each Treatment	165
Table 5.4	The Test Statistic for U-test	165
Table 5.5	Skewness and Kurtosis for the PLM and NPLM	166
Table 5.6	Test of Homogeneity of Variances for PLM and NPLM	168
Table 5.7	The Descriptive Results for PLM and NPLM	168
Table 5.8	The Results of the ANOVA Test for PLM and NPLM	169
Table 5.9	The Skewness and Kurtosis for the Learning Materials in PLM	171
Table 5.10	Test of Homogeneity of Variances for the Learning Materials in PLM	172
Table 5.11	Descriptive Analysis of the Data for the Learning Materials in PLM	173
Table 5.12	The Results of the ANOVA Test for PLM	174
Table 5.13	The Skewness and Kurtosis of the Data for the Learning Materials in NPLM	175
Table 5.14	Test of Homogeneity of Variances for the Learning Materials in NPLM	176
Table 5.15	Descriptive Analysis of the Data	177
table 5.16	The Result of the ANOVA Test for the Learning Materials in NPLM	178
Table 5.17	The Skewness and Kurtosis of the Data for MLM	179
Table 5.18	Test of Homogeneity of Variances	180
Table 5.19	The Descriptive Results for MLM	181
Table 5.20	The Results of the ANOVA Test for MLM	181
Table 5.21	The Skewness and Kurtosis of the Data	182
Table 5.22	Test of Homogeneity of Variances for ULM	183
Table 5.23	The Descriptive Analysis for ULM	184
Table 5.24	The Result of the ANOVA Test for ULM	184
Table 5.25	The Skewness and Kurtosis of the Data for SLM	186
Table 5.26	Test of Homogeneity of Variance for SLM	187

Table 5.27	The Descriptive Analysis for SLM	187
Table 5.28	The Result of ANOVA Test for SLM	188
Table 5.29	The Skewness and Kurtosis of the Data for ILM	189
Table 5.30	Test of Homogeneity of Variance for ILM	190
Table 5.31	The Descriptive Analysis	191
Table 5.32	The Results of ANOVA Test for ILM	191
Table 5.33	The Descriptive Analysis of the Data	195
Table 5.34	Test of Homogeneity of Variances for ILM	197
Table 5.35	Descriptive Analysis of the LGS for each Combination of Independent Variables	198
Table 5.36	Tests of Between-Subjects Effects	199
Table 5.33	Summary of the Data Analysis and Findings of Each Hypothesis	201

LIST OF FIGURES

	Page
Figure 1.1 The Theoretical Framework.....	21
Figure 1.2 The Research Framework	24
Figure 2.1 The ITS Domain (Nwana, 1990).....	62
Figure 2.2 The ITS Model (Nwana, 1990)	63
Figure 2.3 The CBR Cycle (Alves et al., 2008)	82
Figure 2.4 Cognitive Theory of Multimedia Learning (Mayer, 2011).....	93
Figure 3.1 The Model for Design and Development (Alessi & Trollip, 2001).....	101
Figure 3.2 The Functions and Implementations of ITS in ATID	102
Figure 3.3 The Student Model Design	105
Figure 3.4 The Sequence of the Application	111
Figure 3.5 The MLM Design	113
Figure 3.6 The ULM Design	114
Figure 3.7 The SLM Design.....	114
Figure 3.8 The ILM Design.....	115
Figure 3.9 JavaScript Codes in Articulate Storyline	117
Figure 3.10 The Mini Library for MLM	118
Figure 3.11 The Mastery Learning Material	118
Figure 3.12 The Map's Checkpoints	119
Figure 3.13 The Understanding Learning Material	119
Figure 3.14 The Scenes Investigation	120
Figure 3.15 The Park Scene	120
Figure 3.16 The College Registration Scenario	121
Figure 3.17 The Interpersonal Learning Materials.....	121
Figure 3.18 The Animation of the Narrator.....	122

Figure 3.19	Information Required to Construct the New Case	128
Figure 3.20	The Local Similarity Algorithm (Simplified Version)	129
Figure 3.21	The Global Similarity Algorithm (Simplified Version).....	130
Figure 3.22	The Set of New Updated Cases.....	131
Figure 3.23	The Final Output for PLM	132
Figure 3.24	The Final Output for NPLM	132
Figure 4.1	Variables in this Study	137
Figure 5.1	The Shape of the Two Distributions	163
Figure 5.2	The Box-Plot of LGS for Each Treatment	166
Figure 5.3	The Normal Probability Plot of LGS for PLM	167
Figure 5.4	The Normal Probability Plot of LGS for NPLM	167
Figure 5.5	The Box Plot of the Learning Materials for PLM.....	170
Figure 5.6	The Normal Probability Plot of LGS for MLM.....	171
Figure 5.7	The Normal Probability Plot of LGS for ULM.....	171
Figure 5.8	The Normal Probability Plot of LGS for SLM	172
Figure 5.9	The Normal Probability Plot of LGS for ILM	172
Figure 5.10	The Box-Plot of the Learning Materials for NPLM.	174
Figure 5.11	The Normal Probability Plot of LGS for MLM.....	175
Figure 5.12	The Normal Probability Plot of LGS for ULM.....	175
Figure 5.13	The Normal Probability Plot of LGS for SLM	176
Figure 5.14	The Normal Probability Plot of LGS for ILM	176
Figure 5.15	The Box-plot of LGS for Each Treatment	178
Figure 5.16	The Normal Probability Plot of LGS for PLM	179
Figure 5.17	The Normal Probability Plot of LGS for NPLM	180
Figure 5.18	The Normal Probability Plot of LGS of NPLM.....	182
Figure 5.19	The Normal Probability Plot of LGS for PLM	183
Figure 5.20	The Normal Probability Plot of LGS of NPLM.....	183

Figure 5.21	The Box-Plot for PLM and NPLM of SLM.....	185
Figure 5.22	The Normal Probability Plot of LGS for PLM	186
Figure 5.23	The Normal Probability Plot of LGS for NPLM	186
Figure 5.24	The Box-Plot for PLM and NPLM of ILM.....	189
Figure 5.25	The Normal Probability Plot of LGS for PLM	189
Figure 5.26	The Normal Probability Plot of LGS for NPLM	190
Figure 5.27	The Box-plot for MLM-PLM	192
Figure 5.28	The Box-plot for MLM-NPLM	192
Figure 5.29	The Box-plot for ULM-PLM	193
Figure 5.30	The Box-plot for ULM-NPLM	193
Figure 5.31	The Box-plot for SLM-PLM.....	193
Figure 5.32	The Box-plot for SLM-NPLM.....	193
Figure 5.33	The Box-plot for ILM-PLM.....	194
Figure 5.34	The Box-plot for ILM-NPLM.....	194
Figure 5.35	The Normal Probability Plot of LGS for MLM-PLM	195
Figure 5.36	The Normal Probability Plot of LGS for MLM-NPLM	195
Figure 5.37	The Normal Probability Plot of LGS for ULM-PLM	196
Figure 5.38	The Normal Probability Plot of LGS for ULM-NPLM	196
Figure 5.39	The Normal Probability Plot of LGS for SLM-PLM.....	196
Figure 5.40	The Normal Probability Plot of LGS for SLM-NPLM.....	196
Figure 5.41	The Normal Probability Plot of LGS for ILM-PLM.....	197
Figure 5.42	The Normal Probability Plot of LGS for ILM-NPLM.....	197

LIST OF EQUATIONS

	Page
Equation 2.1 Local Similarity Formula	86
Equation 2.2 Global Similarity Formula	86
Equation 4.1 KR20 Formula	146

LIST OF ABBREVIATIONS

PLM	Personalized Learning Material
NPLM	Non-Personalized Learning Material
MLM	Mastery Learning Material
ULM	Understanding Learning Material
SLM	Self-Expressive Learning Material
ILM	Interpersonal Learning Material
ATID	Alessi and Trollip's Instructional Design
CSS	Case-based Reasoning Similarity Score
LGS	Learning Gains Score
MLSI	Math Learning Style Inventory
TIMMS	Trends in International Mathematics & Science Study
PISA	Programme for International Student Assessment
MOE	Ministry of Education
EPU	Economic Planning Unit
MQA	Malaysia Qualification Agency
SPM	Sijil Pelajaran Malaysia

LIST OF SYMBOLS

Σ	Summation
$f_{(N)}$	Feature related to a new case
$f_{(K)}$	Feature related to a stored case
w_i	Significance weight of a feature
$sim()$	Similarity function of a feature
df	Degree of freedom
F	F statistic or F -value
M	Mean
n	Sample size (sub-sample)
N	Sample size (full sample)
SD	Standard Deviation
SE	Standard Error
T	t -value
z	z-score
$KR20$	Kuder-Richardson Formula 20
p	Proportion of correct responses to test items
q	Proportion of incorrect responses to test items
σ^2	Variance
η^2	A measure of effect size

**PEMBANGUNAN DAN PENILAIAN BAHAN PEMBELAJARAN TERSUAI
DIRI DENGAN MENGGUNAKAN ALGORITMA PEMPROFILAN UNTUK
PELAJAR POLITEKNIK DALAM PEMBELAJARAN ALGEBRA**

ABSTRAK

Matematik adalah asas untuk pengajian kejuruteraan, terutamanya bagi pelajar kejuruteraan di politeknik Malaysia. Topik algebra pula adalah topik penting dalam matematik terutama bagi program kejuruteraan. Kajian-kajian lepas menunjukkan teknik pembelajaran tersesuai diri mampu meningkatkan kefahaman pelajar. Oleh itu, kajian ini dilakukan untuk mereka bentuk dan membangunkan satu aplikasi menggunakan teknologi Sistem Tutor Pintar (STP) untuk pembelajaran tersesuai diri bagi pembelajaran matematik. Teknologi ini membantu pembelajaran tersesuai diri dengan memberi cadangan bahan pembelajaran paling sesuai. Cadangan ini dilakukan melalui pengiraan algoritma Penaakulan Berasaskan Kes (PBK) dengan mencari persamaan antara profil baru dan profil yang disimpan di dalam pangkalan data. Cadangan dari profil yang mempunyai nilai persamaan paling tinggi digunakan sebagai rujukan. Gaya pembelajaran dan pengetahuan awalan pelajar digunakan sebagai maklumat untuk membentuk profil pelajar. Terdapat dua versi bahan ujian yang dibina: Pembelajaran Tersuai Diri (PTD) yang merujuk pelajar kepada nilai profil persamaan paling tinggi dan Pembelajaran secara Bukan Tersesuai Diri (PBTD) yang merujuk kepada nilai profil persamaan paling rendah. Terdapat empat bahan pembelajaran yang telah dibina dalam kajian ini iaitu Bahan Pembelajaran secara Masteri (BPM), Bahan Pembelajaran secara Pemahaman (BPP), Bahan Pembelajaran secara Ekspresi Diri (BPED) dan Bahan Pembelajaran secara Interpersonal (BPI). Ketepatan aplikasi yang dibina dalam memberikan cadangan

bahan pembelajaran diukur menggunakan pengiraan Skor Persamaan PBK (SPP) dan pencapaian pelajar diukur menggunakan pengiraan Skor Pencapaian Pembelajaran (PP). Data daripada 309 orang pelajar semester satu dianalisis menggunakan ujian statistik Mann-Whitney U dan ANOVA. Dapatan kajian menunjukkan aplikasi yang dibina memberikan cadangan berdasarkan pengiraan algorithma PBK dan nilai PP bagi pelajar yang menggunakan versi PTD adalah lebih baik berbanding pelajar yang menggunakan versi PBTD. Hasil kajian juga menunjukkan para pelajar yang menggunakan bahan pembelajaran BPI mempunyai SPP yang paling tinggi berbanding bahan pembelajaran yang lain. Teori pembelajaran berbilang media, model reka bentuk bahan pembelajaran dan algorithma PBK berjaya digabungkan dalam satu STP untuk menghasilkan aplikasi pembelajaran tersesuai diri yang berkesan. Sehubungan itu, dapatlah disimpulkan bahawa kajian ini telah berjaya membangunkan aplikasi yang berjaya meningkatkan pencapaian pelajar dalam algebra.

**THE DEVELOPMENT AND EVALUATION OF PERSONALIZED
LEARNING MATERIAL BASED ON A PROFILING ALGORITHM FOR
POLYTECHNIC STUDENTS IN LEARNING ALGEBRA**

ABSTRACT

Mathematics is the foundation for engineering studies, especially for Malaysian polytechnics engineering students. Algebra is an important topic in mathematics, especially in engineering programs. Previous research shows that personalization techniques can increase student understanding. Thus, the aim of this study was to design and develop an application that utilized Intelligent Tutoring System (ITS) technology for the personalization of mathematics learning. This technology has the ability to help with the personalization of student learning by recommending the most suitable learning materials. The recommendation is computed using a Case-based Reasoning (CBR) algorithm by finding the similarity between the new submitted profile and the stored profiles in the database. The solution given by the most similar cases is used as a reference. Prior learning and mathematics learning style are the two parameters of a student's profile. The ITS formed two versions of treatments: Personalized Learning Material (PLM) and Non-personalized Learning Material (NPLM). The PLM presented a learning material by referring to a solution from the most similar case to the newly submitted case and the Non-personalized Learning Material (NPLM) referred to a solution from the least similar case. The four learning materials developed for this study were Mastery Learning Material (MLM), Understanding Learning Material (ULM), Self-Expressive Learning Material (SLM) and Interpersonal Learning Material (ILM). The accuracy of the recommendation was measured using the CBR Similarity Score

(CSS) and the learning performance was measured using the Learning Gain Score (LGS). The data from 309 first semester engineering students was analyzed using the Mann-Whitney U test and ANOVA. The results show that the recommendations were generated based on the calculations by the CBR algorithm and the PLM groups have greater LGS than the NPLM groups. The ILM group obtained higher LGS than those working with other groups of learning materials. Guided by the cognitive theory of multimedia learning and instructional design model, the CBR algorithm was successfully integrated with the ITS components to produce an effective personalized application. This study has thus successfully developed a learning application that effectively increases student performance in algebra.

CHAPTER ONE

INTRODUCTION

1.1 Introduction

The field of instructional technology has continuously looked to improve the effectiveness of instructional and learning materials. The learning materials that use the theory of instructional technology have the ability to provide flexibility in learning and to cater to the diverse needs that exist in every classroom (Karich, Burns, & Maki, 2014). Previous studies (e.g. Chiu & Churchill, 2015a; Sparapani & Calahan, 2015; Williams, 2015) have discussed the effectiveness of using instructional technology in assisting students' learning. Science (Butler, Marsh, Slavinsky, & Baraniuk, 2014), English (Liu, Navarrete, & Wivagg, 2014), and mathematics (Abramovich & Connell, 2014) are among the subjects that have been improved with instructional technology learning materials

Over the years, various researchers around the world have stressed the importance of mathematics (e.g. Ganai & Guiab, 2014; Hodgen & Marks, 2013; Jasni & Zulikha, 2013; Samkange, 2015). As a basic pillar of scientific knowledge, mathematical competence acts as an important foundation for workplace requirements. An international report by the Education and Training Foundation (2015) concluded that the majority of employers requested that their future employees obtain basic mathematical skills, and have the ability to accommodate their mathematical understanding to work requirements. The report also suggested that there is single no standard that can be considered the most appropriate approach

to teaching and learning mathematics. Nevertheless, all the studies reviewed in the report agreed on the importance of tailoring learning to the specific learners.

A lack of mathematical competence will result in misinterpretation and incorrect application in mathematics, especially when related to science and engineering studies (Hodgen & Marks, 2013). Malaysia is currently on the way to achieving its mission to be a high income economy by the year 2020 (Economic Planning Unit [EPU], 2010). This can only be accomplished with a highly skilled community who are able to improve their knowledge in both the technical and professional fields. Mathematics competency is thus deemed very important in the process of producing competent workers.

Hogan (2014) suggested that educational institutions have to find and provide the most suitable pedagogical approach for mathematics, in order to be on a competitive level with leading countries such as Singapore, South Korea and China. However, the 2011 report from the Trends in International Mathematics & Science Study (TIMSS), which is designed to assess the quality of the teaching and learning of mathematics and science among participating countries, showed that Malaysia's rank and average scores in mathematics fell from the 20th place in 2007 to 26th in 2011 (International Association for the Evaluation of Educational Achievement, 2012).

The Programme for International Student Assessment (PISA) 2012 ranked Malaysia 52 out of 65 countries (Organization for Economic Co-operation and Development [OECD], 2013). PISA is a worldwide study to assess student performance in mathematics, science, and reading. The average mark for mathematics was 494, and Malaysia managed to score only 421, well below the

average. These poor results have drawn the attention of academicians to the quality and achievements of our students in mathematics.

The results from both international organizations provide a brief overview of the level of mathematics achievement in secondary school leavers. About 37.2 percent of these students will eventually further their study in polytechnics, colleges and universities (World Education Service, 2015). Recent studies in a Malaysian context by Khalid and Yamin (2013) and Ngasiman (2014) concluded that most of these students remain weak in mathematics, even after eleven years of mathematics education. Their research found that some students struggled in mathematics during their tertiary study, although they had passed mathematics in the Sijil Pelajaran Malaysia (SPM) or the Malaysian Certificate of Education. The SPM is internationally equivalent to the GCSEs in England and Wales. These issues will potentially have a great effect on the process of producing competent workers, and will therefore slow economic growth.

Mathematics has been specifically mentioned in various educational reports and plans, such as the National Higher Education Action Plan Phase 2 (2011 - 2015) (Ministry of Education (MOE), 2011), 11th Malaysian Plan (EPU, 2015) and the Malaysia Education Blueprint (MOE, 2015). These reports stress the need to focus more on improving the mathematical achievement of Malaysian undergraduates in order to produce more competent workers, especially in fields that are related to science and engineering. As mathematical concepts are important for mathematics-related subjects, most students with low mathematics achievement have faced difficulties in their studies (Alves, Rodrigues, Rocha, & Coutinho, 2013). Various studies (such as those by Hodgen & Marks, 2013; Max & Alessandro, 2012; Omar,

Bakar, & Mat Rashid, 2014) have linked mathematical competency with the ability to excel in engineering fields.

Low achievement in mathematics will normally have an impact on the overall process of producing competent graduates. Graduates from technical institutions in Malaysia will fulfill most of the job requirements in technical fields (EPU, 2015). These technical institutions thus have the obligation to produce technical workers who can comply with the requirement of the jobs offered to them. The perspective of educators and curriculum developers should thus include the achievement of mathematical skills among students in technical institutions.

Researchers such as Albano, Miranda, and Pierri (2015), Awofala (2014) and Zhang and Stephens (2013) suggest the application of the personalization technique as one of the options to improve student achievement in mathematics. This technique uses information about individual differences to deliver the most suitable learning materials for a specific student (Awofala, 2014). The process of implementing the personalization technique in any educational institution is time-consuming, however, requires tedious work and is not cost effective (Green, 2013). The Intelligent Tutoring System (ITS) has thus been seen as the most suitable technology for the application of personalization techniques. Various researchers such as Arroyo et al., (2014), Koedinger, Anderson, Hadley, and Mark (1997), and Melis and Siekmann (2004) have successfully developed applications based on ITS that helped the personalization of student learning.

Although the ITS is an instructional technology product that have proven to be efficient to assist in personalization process, the development and application of the technology have yet to be applied in Malaysian polytechnic setting. There were

also lacking of studies on the effect of using this technology to the students' mathematical performances by utilization of information of the student profiles. Thus, the researcher believed that developing an ITS that personalizes mathematics learning is worthwhile and investigating its effect on students' mathematics performance is of utmost importance.

1.2 Background of the Study

The Malaysian government has increased their effort in the establishment of polytechnics, community colleges and other technical training centers (Omar, et al., 2014). Polytechnics, which are under the Department of Polytechnic Education (DPE) of the Ministry of Education are technical education institutions that are responsible for supplying semi-skilled technical workers for the country (Ministry of Education, 2014). The 11th Malaysian Plan estimated that 60% of the 1.5 million job opportunities that will be introduced in 2016 are related to Technical and Vocational Education and Training (TVET) (EPU, 2015).

Studies by Khalid and Yamin (2013) and Halim, Abdul, and Haron (2014) suggest that the quality of teaching and learning in polytechnics is questionable, however, when polytechnic graduates cannot perform well at the university level when continuing their education. Omar et al. (2014) suggested that polytechnics must ensure that their students have the employability skills needed by the industry. Mathematics for engineering students is often regarded as a language in the world of engineering Tawil et al., (2012), and it is therefore important that every graduate from the engineering courses in a polytechnic has the ability to apply mathematical knowledge and to be able to understand mathematical concepts, especially related to engineering.

Although mathematics is highlighted in various reports and guidelines, previous studies on the achievement of polytechnic students in mathematics show intriguing results. A study by Halim et al. (2014) with final year polytechnic engineering students showed mistakes in questions related to the understanding of basic algebra. According to the analysis, the main mistakes these students usually make stem from the misconception of the algebraic fraction, failure to use the factorization technique and misconception of polynomial algebraic problems. This is supported by Hussin and Ramli (2014), which suggested that polytechnic students were having difficulties in mathematics-related subjects when they had a low understanding of basic algebra. It can be concluded that the mistakes, misconceptions and the difficulties in learning mathematics stem from a poor understanding of basic algebra.

Whenever mathematics is discussed, algebra receives the most attention. Algebra is the building block for success in mathematics (Max & Alessandro, 2012; Star et al., 2014). According to a report by Hodgen and Marks (2013), the mathematical contents that are needed for the workplace are: (i) numbers, (ii) statistics and probability, (iii) algebra, and (iv) geometry and measurement. Among these contents, algebra plays the most important role, especially in engineering. This topic is greatly needed in the mathematics, engineering and science fields. Kooij and Goddijn (2010) also noted that algebra is present in higher levels of vocational classrooms where mathematics, engineering and science are applied. A study by Pyzdrowski et al. (2013) concluded that for a student to succeed in an engineering program they need to excel in calculus, which stems from a strong background in algebra.

Correspondingly, certain measures must therefore be taken by the curriculum developers and educators in polytechnics to increase mathematics achievement. The study by Halim et al. (2014) demonstrated that there is a significant increase in the achievement of polytechnic students in mathematics when the personalization technique is applied in a mathematics classroom. A study by Areelu and Akinsola (2014) also supported the personalization technique by concluding that the technique has significantly increased mathematics achievements, especially for those with low achievement. This is supported by Zhang and Stephens (2013) who stated that personalization helps educators to efficiently differentiate mathematics learning among students. The process of attending to individual learning needs eventually increases the performance of the whole class.

Although the ability of the personalization technique to improve learning has been acknowledged, the process of implementing this technique in actual classroom settings is challenging. As stated by Patrick, Kennedy, and Powell (2013), for personalization to be successfully carried out, the organization, educators, and students must be facilitated with a suitable instructional strategy and technology. This is supported by Karich et al. (2014), who argue that the diversity of students increases the need for personalized learning material that uses the instructional technology theory. Therefore, researchers (e.g. Klašnja-Milićević, Vesin, Ivanović, & Budimac, 2011; Narciss et al., 2014; Tseng, Chu, Hwang, & Tsai, 2008) have suggested using ITS as the most suitable instructional technology to assist in the implementation of the personalization technique.

For the purpose of personalizing student's learning, the attributes that comprise the student's profile should be the main consideration. Researchers and

educators have been developing many personalized learning applications based on attributes such as a student's personal information, learning portfolios, learning tracks and learning styles (Hwang, Han-yu, Hung, Huang, & Tsai, 2012; Mahnane, Laskri, & Trigano, 2013; Rtili, Dahmani, & Khaldi, 2014). The use of information technology to accommodate personalization has been of great interest to researchers and practitioners, especially in the Intelligent Tutoring System (ITS) development process (Sani & Teh, 2014). A personalized learning application must have the human-like ability to present learning material that matches the student's preferences with the aim of making the learning process more effective.

An experiment by Yang, Hwang and Yang (2013) showed that, by using information about a student's learning style and cognitive attributes in the design of personalized learning material, better results can be obtained. This was supported by Albano et al. (2015) in their research, who noted that the personalization of a learning process that considered both cognitive attributes and learning style can lead to achievable outcomes in learning mathematics. It is therefore important for information on a student's learning style and their cognitive attributes to be included for personalization purposes.

The importance of accommodating a student's learning style in developing learning materials was noted in Star et al. (2014). Their research suggested that students whose learning style is accommodated could achieve a 75% standard deviation higher than students who are not accommodated. The Mathematics Learning Style theory by Strong, Thomas, Perini, and Silver (2004) documented four learning styles, which stem from Carl Jung's learning preferences. This learning style was used in the Math Learning Style Inventory (MLSI) (Silver, Thomas, &

Perini, 2008). The four learning styles are mastery, understanding, self-expression and interpersonal. Every human being is born with the ability to use all four, but each person has preferences for one style over another (Klašnja-Milićević et al., 2011).

In view of providing an understanding of the students' cognitive preferred way of learning mathematics, the Math Learning Style Inventory (MLSI) is the most appropriate learning inventory compared to other learning style inventories. The Myer-Briggs Type Indicator (Myers & Myers, 1995) and Kolb's Learning Style Inventory (Smith, 2010) are examples of learning inventories that are not focused specifically on mathematics learning.

Although the information on the students' learning style is important, the students' prior knowledge is a cognitive attribute that should also be considered in the personalization of student learning. As suggested by Booth, Newton, and Twiss-Garrity (2014) and Mampadi, Chen, Ghinea, and Chen (2011), a student's prior knowledge is important for mathematics learning to take place. This is supported by Aniban and Elipane (2014), who suggested that the effort of directing learning in mathematics, especially algebra, must be through identifying prior knowledge. According to Hailikari (2009), test results can be a method to assess a student's prior knowledge. The past examination result of these polytechnic students can be used as information reflecting their prior knowledge.

Nevertheless, the process of utilizing the information on a student's profile to personalize their learning materials can be a complicated and time-consuming task. Therefore, educators and researchers have recommended and applied artificial intelligence (AI) techniques. Among the AI techniques that have been applied in

various ITS are Fuzzy Logic (Narlı, Özgen, & Alkan, 2011), Genetic Algorithms (Huang, Huang, & Chen, 2007) and Case-based Reasoning (CBR) (Cocca & Magoulas, 2012). CBR is an AI algorithm that uses previous experience to solve current problems (Aamodt & Plaza, 1994). It has the ability to provide a solution to a new problem that is submitted to the ITS application by finding a similar past case.

The CBR algorithm is based on cases and patterned by the way people solve problems by retrieving information from previous experience in order to reason for the current situation (Yang & Yan, 2011). A case is a set of problems or profiles with a solution or a recommendation. By retrieving and matching new cases with similar results from the database, a suitable and more personalized learning material can be suggested to the students. The CBR algorithm is thus the most suitable approach for aiding the development of ITS for mathematics learning. This algorithm has been applied in various ITS such as TOPOLOR (Salem & Hisham, 2013), PERSO (Chorfi & Jemni, 2004) and eXpresser (Cocca & Magoulas, 2012).

In light of applying the CBR algorithm in the ITS architecture of the developed application for this study, personalized learning materials can be presented to students effectively. Together with this, the information from the students' profiles can be used by the ITS as recommendation criteria for personalized learning. Thus, the study of the effect of this ITS on students' mathematics achievement is crucial in gaining a better understanding of the most suitable instructional technology for personalized learning. Furthermore, this study can give more insight on the importance of accommodating student attributes in learning mathematics. This will eventually address the issues related to low

achievement in mathematics among polytechnic students and fulfill the needs for personalized learning material for mathematics learning.

The study on the effectiveness of the learning materials developed in this paper also contributes to the knowledge of instructional technology. In algebra learning, it is important that students are provided with a learning environment that can stimulate their cognitive ability in the process of understanding an algebra concept (Chiu & Churchill, 2015). The learning materials developed in this study by applying the principles of multimedia learning and using an instructional design model can be added value in understanding the effects of instructional technology learning materials in improving students' mathematics learning.

1.3 Preliminary Study

A preliminary study was carried out in five phases to obtain information about algebra learning from the perspectives of the students and the lecturers in Malaysian polytechnics. Primarily, this preliminary study was done to get an overview of the algebra performance of students and information on the factors that may affect their performance in algebra. In addition, this preliminary study aimed to get some points of view from lecturers regarding the teaching and learning of algebra. Three groups of students were randomly chosen from the semester one students who enrolled for the June 2013 session. The first group was given a set of surveys, the second group was given an algebra test, and the last group was given the MLSI. Past examination results were also used as additional information regarding the algebra performance of polytechnic students. Table 1.1 shows the method of the preliminary study and the purposes of each phase of the preliminary study. All results from this section are provided in Appendix A.

Table 1.1

Method and Purpose of the Five Phases of Preliminary Study

Phase	Method	Purpose
1	Analysis of final examination results	To measure student levels of achievement in mathematics
2	Survey	To identify the issues or problems related to mathematics learning from the student perspective
3	Interview with mathematics lecturers	To discover the issues or problems related to mathematics learning from the lecturers' perspective
4	Algebra test	To measure student understanding of certain subtopics
5	MLSI	To determine the learning style distribution

The results from this preliminary study give an overview of the achievement of the semester one polytechnics students for the topic of algebra. It can be concluded from the algebra test result and examination results that the achievements of polytechnic students in Engineering Mathematics 1 was at the minimum level of grade C (Ministry of Education [DPE], 2014). In order to excel in engineering programs, the students who enroll must obtain good results in mathematics (Tague, Czochoer, Baker, & Harper, 2013). For polytechnics, a good result is when the students obtain at least grade B (Ministry of Education, 2014).

Moreover, the students claimed in the survey given that the traditional classes did not currently cater for student differences, and that they need additional tutoring to help them in their mathematics study. The survey results were supported by the results of the interviews with the lecturers, in which the majority agreed on the need for personalized learning material to cater to students' differences that exist in every classroom. In addition, the results from the MLSI assessment proved that there are clearly different preferences for mathematics learning styles among these polytechnic students.

1.4 Problem Statement

In engineering related studies, the failure to master the concept of algebra can lead to low achievement since algebra is the gatekeeper to higher levels of mathematics (Hodgen & Marks, 2013). An examination report by Ibrahim et al., (2011) as well as studies by Ismail and Ahmad (2012) and Khalid and Yamin (2013) showed that most polytechnic students still fail to master the topic of algebra. The preliminary study also clearly showed that polytechnic students had low achievement in this topic. The polytechnic lecturers who were interviewed also expressed their agreement about these low achievements. The polytechnic students were also found to be struggling to solve questions related to algebra in tests.

Consequently, the personalization technique is the most suitable learning technique to address the issue of low algebra performance based on previous studies and interviews with the polytechnic lecturers. However, to enable the personalization technique to be used effectively, the students' attributes must be included in the personalization of the students' learning. Researchers (e.g. Lee & Chen, 2014; Miliband, 2006; Patrick, Kennedy, & Powell, 2013) agree on the importance of accommodating a student-preferred learning style and a student's prior knowledge in the process of personalization. The Math Learning Style Inventory (MLSI) by Silver et al. (2008) is thus deemed suitable for assessing student preferences in learning mathematics. The information on a student's mathematics learning style and a student's prior knowledge are both used to create a learning profile. This information is used to determine the most suitable learning strategy for the personalization of mathematics learning.

In order to effectively personalize a student's learning, the ITS is a product of instructional technology that enabled educational material to be personalized according to learner profiles, and to ease the personalization process (Rtili et al., 2014). CBR is also one of the AI algorithms that has many advantages when applied in ITS development (Alves et al., 2013; Kolodner, 2014). The algorithm functions by proposing the appropriate learning material for every student based on a solution from previous cases. In this research, a CBR application was developed to personalize mathematics learning based on the student learning profiles.

While the concept of personalization of a student's learning in the mathematics classroom is not new, the field is still lacking empirical validation. Although the learning style theory has been applied in various ITS developments, the reviews of previous studies by Özyurt and Özyurt (2015) as well as by Truong (2015) demonstrated that none of the applications used mathematics learning style as one of the parameters for the learning profile. Moreover, the pairing of prior knowledge and mathematic learning style is lacking in previous studies. Added to that, the technology of ITS and the concept of personalized learning has not yet been discussed and applied in Malaysian polytechnics. The use and effectiveness of learning material, especially mathematics learning materials that are personalized to a specific profile, has also not yet been measured. It is therefore important to measure the effectiveness of an ITS that has the ability to personalize a polytechnic student learning profile.

1.5 Purpose of the Study

The purpose of the study is to develop a personalized, intelligent tutoring system that has the ability to suggest suitable learning material based on predefined

profiles: (i) mathematics learning styles and (ii) prior knowledge. By using a CBR algorithm and information from the student's profile, suitable learning material is presented. The accuracy of the developed system in giving recommendations was measured by calculating the CBR Similarity Score (CSS). For every learning session, the students were tested with pretest and posttest questions to measure the learning gain score of the students when presented with these learning materials.

This study involves quasi-experimental research on the effect of four learning materials: (i) Mastery Learning Material (MLM), (ii) Understanding Learning Material (ULM), (iii) Self-Expressive Learning Material (SLM) and (iv) Interpersonal Learning Material (ILM) on the algebra performances of the students. This study also investigated the effect of the learning materials in the personalization of mathematics learning in two types of treatments. The first treatment is Personalized Learning Material (PLM), which functions by presenting the learning material that is mapped to a student profile. Conversely, the second treatment is Non-Personalized Learning Material (NPLM), and functions by presenting learning material that is not mapped to their profile.

1.6 Research Objectives

The objectives are formulated to overcome the problems and further answer the research questions. The main objective of this study is to design and develop an ITS application that can accurately present suitable learning material based on a student's profile, as well as to measure the effect of the developed application on students learning performance in mathematics. To achieve this, the following specific objectives must be accomplished.

- i) Develop an application with an artificial intelligence algorithm; Case-based Reasoning that has the ability to personalize the learning material suited for every profile submitted to the application.
- ii) Investigate whether the developed application successfully recommended the most suitable learning material based on the submitted profiles.
- iii) Investigate the effects of each learning treatment (Personalized Learning Material and Non-Personalized Learning Material) on the algebra performances of the students.
- iv) Study the effects of four modes of learning materials (Mastery Learning Material, Understanding Learning Material, Interpersonal Learning Material and Self-Expressive Learning Material) on the algebra performances of the students in each treatment group.

1.7 Research Questions

This study is designed to specifically address this set of questions:

- i. Is there a significant difference between PLM and NPLM in the CBR Similarity Score?
- ii. Is there a significant difference between PLM and NPLM in student algebra performances?
- iii. Are there significant differences between MLM, ULM, SLM and ILM in student algebra performances for the PLM group?
- iv. Are there significant differences between MLM, ULM, SLM and ILM in student algebra performances for the NPLM group?
- v. Is there any significant difference between PLM and NPLM in the algebra performances of the students presented with MLM?

- vi. Is there any significant difference between PLM and NPLM in the algebra performances of the students presented with ULM?
- vii. Is there any significant difference between PLM and NPLM in the algebra performances of the students presented with SLM?
- viii. Is there any significant difference between PLM and NPLM in the algebra performances of the students presented with ILM?
- ix. Is there any significant interaction between learning material and treatment for the algebra performances of the students?

These research questions were developed to enable the Research Objectives listed before can be achieved in this study. Thus, Research Question 1 is specifically developed to achieve Research Objective 1 and 2, Research Question 2 to 4 are aiming to achieve Research Objective 3, and Research Question 5 to 9 are to achieve Research Objective 4.

1.8 Research Hypotheses

The following hypotheses were formulated from the above research questions. The probability level of 0.05 will be used to test for statistical significance.

- H₀1: There is no significant difference between PLM and NPLM in CBR Similarity Score.
- H₀2: There is no significant difference between PLM and NPLM in student Learning Gain Score.
- H₀3: There are no significant differences between MLM, ULM, SLM and ILM in student Learning Gain Score in the PLM group.
- H₀4: There are no significant differences between MLM, ULM, SLM and ILM in student Learning Gain Score in the NPLM group.

- H₀5: There is no significant difference between PLM and NPLM in the Learning Gain Score of students presented with MLM.
- H₀6: There is no significant difference between PLM and NPLM in the Learning Gain Score of the students presented with ULM.
- H₀7: There is no significant difference between PLM and NPLM in the Learning Gain Score of the students presented with SLM.
- H₀8: There is no significant difference between PLM and NPLM in the Learning Gain Score of the students presented with ILM.
- H₀9: There is no significant interaction between learning material and treatment for the Learning Gain Score of the students.

1.9 Significance of the Study

This study developed a learning application that can provide personalization for mathematics learning. Personalization in the learning of mathematics is important to increase student achievement. The personalization technique that was applied in this study involves presenting the student with learning materials that suited their learning style and mathematics achievement.

The best way to make personalization work for the greatest number of students is by using ITS. This study will also measure the ability of the CBR algorithm to give suggestions on appropriate learning material based on previous cases. The previous cases consisted of learning profiles and the selected learning materials of students. The process is important in order for the system to intelligently adapt and ensure that users' needs are met. The functionality of an ITS involves being able to precisely adjust the individual learning by recommending the appropriate learning material for every student.

Although many applications have been developed based on the concept of personalization in learning, most are in the field of e-learning. There are a few studies on mathematics learning, but none applied the Mathematics Learning Styles by Strong et al. (2004). In the field of AI, this study provides additional input on the development of ITS for mathematics learning. The information on student learning styles and mathematics achievement was used by the developed application to determine the most suitable learning material assisted by the CBR algorithm. Thus, this study gives new insight into ITS research and development.

This study investigated the applicability of using specific learning material in a standard first semester classroom. Every student involved was exposed to four learning materials and their performance in algebra was measured. The findings contributed to further understanding the effectiveness of personalization in the mathematics classroom. The study of learning materials that are developed based on the four learning styles can be used as an important tool in the teaching and learning process.

The outcome of study has the potential to contribute to the mathematics education field where educators can apply the findings from these results to improve mathematics education in polytechnics. By improving the learning of mathematics, student achievement can also be improved. It is crucial for engineering students to achieve a good grade in mathematics and to be literate in mathematics because engineering field is where mathematics has been widely applied.

The stakeholders in this research are the curriculum developers, lecturers, and students, and this research has various impacts on several issues. Curriculum developers can obtain insights into whether learning style preference and prior

knowledge have an effect on a student's learning style. By identifying student preferences, the curriculum developers can develop a personalized learning curriculum that caters for individual differences. The output of this study can also provide information on the teaching strategies that lecturers can apply when they encounter students with different preferences in classes. The advantage of this research for students is that it provides an opportunity to identify student learning preferences with more personalized learning that caters for student differences.

1.10 Theoretical Framework

The theoretical framework in Figure 1.1 shows the theories, method, and models that work as the foundation of this study. The Mathematics Learning Style by Strong et al. (2004) and Cognitive Theory of Multimedia Learning (CTML) by Mayer (2011) are the fundamental theories used in this study. The ITS was developed by applying a CBR algorithm. The instructional design and development process applied the Alessi and Trollip Instructional Design (ATID) Model by Alessi and Trollip (2001) and the ITS Architecture (Nwana, 1990).

The design and development part of the application for this study followed the guidelines for the CTML and ATID models. The instructional learning material for mathematics learning was developed based on learning strategies that were guided by the Mathematics Learning Style Theory. Whenever an ITS is in discussion, the architecture of an ITS must be included in the design and development process. Finally, the heart of the application, the AI methodology, is implemented by the CBR algorithm. All these theories, methods, and models work together simultaneously to provide effective ITS application for personalization of mathematics learning.

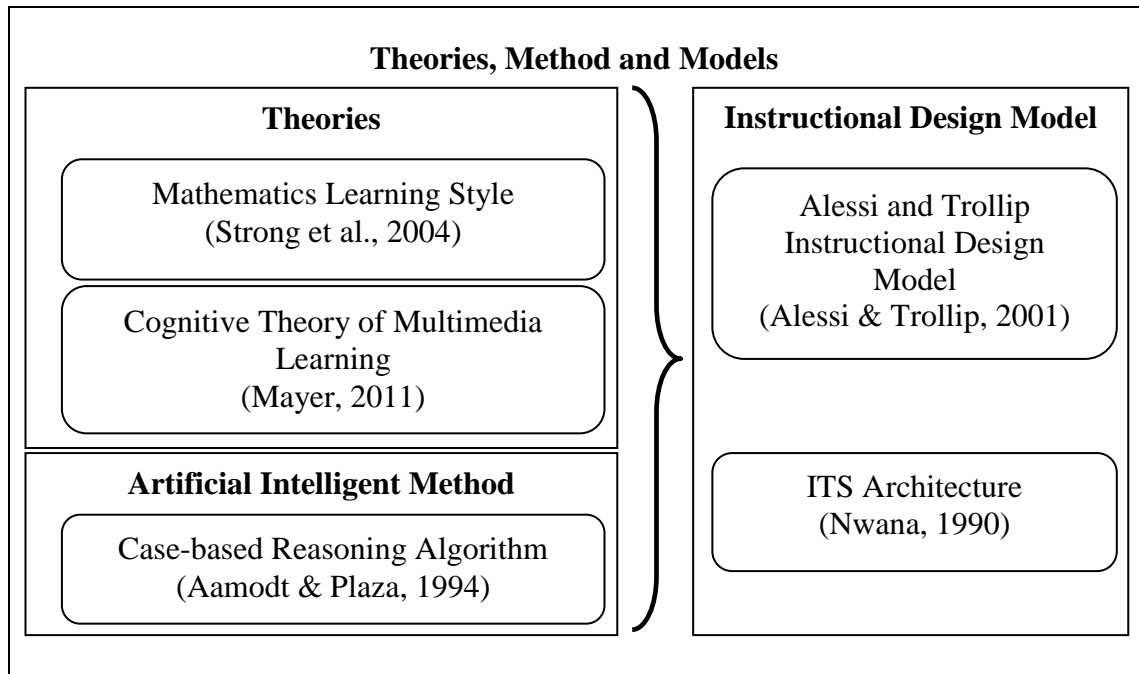


Figure 1.1. The Theoretical Framework

1.10.1 Case-based Reasoning Algorithm

The CBR algorithm has been adapted in the theoretical framework, and acted as an intelligent tool that functions to calculate the similarity value of the new learning cases or problems submitted to the application with stored cases in the database. Problems are solved by using similar knowledge of previous cases. The CBR algorithm is applied in the application development because of its ability to intelligently offer the prediction of a specific solution based on previous data.

1.10.2 Alessi and Trollip's Instructional Design Model

According to Alessi and Trollip (2001), the process of facilitating learning must include several activities; presenting the information, guiding the learner, practicing and assessing learning. By using these guidelines, instructional activities should take place effectively and efficiently. This model will act as a guide in developing the learning materials for the application.

1.10.3 Mathematics Student Learning Style

The mathematics learning style suggested by Strong et al. (2004) was used in the design of the learning materials in this application. The learning materials have four distinct styles:

- a) Mastery Learning Style (MLS) that emphasize skill acquisition and the retention of critical mathematical terms.
- b) Understanding Learning Style (ULS) that builds a student's capacity to find patterns and explain mathematical concepts.
- c) Self-Expressive Learning Style (SLS) that capitalizes on student powers of imagination and creativity.
- d) Interpersonal Learning Style (ILS) that invites students to find personal meaning in mathematics.

1.10.4 Mayer's Cognitive Theory of Multimedia Learning

This theory explains that humans learn from words and pictures and how the information is processed through two basic channels: verbal and visual. This theory proposed twelve research-based principles for the design of the multimedia application that is discussed further in Chapter Two. Multimedia design principles provide guidelines for making use of a combination of words and pictures rather than using only text in the design.

1.10.5 ITS Architecture

The ITS is designed with the idea of providing learning through the utilization of AI techniques. The architecture of an ITS basically consists of the

Domain Model, Student Model, Tutorial Model and User Interface Model. These models interact to provide the knowledge that the students require.

1.11 Research Framework

The independent variable consisted of four modes of learning materials, (i) MLM, (ii) ULM, (iii) SLM, and (iv) ILM grouped into two types of treatments (i) PLM and (ii) NPLM, as shown in Figure 1.2. The PLM is where the selected learning material is mapped to the student profile. NPLM is the selection of learning material that is randomly assigned to the student. The dependent variables for this study are the CBR Similarity Score (CSS) and Learning Gain Score (LGS).

1.11.1 PLM and NPLM

The two treatments developed for this study are Personalized Learning Material and Non-personalized Learning Material. These treatments were to test the accuracy of the application in giving recommendations of the most suitable learning material, and to test the effectiveness of presenting a learning material that is mapped to a student's profile.

1.11.2 Case-based Similarity Score

One of the dependent variables for this study is the Case-based Similarity Score (CSS) that was developed to measure the accuracy of the application developed in this study to give recommendations of the most suitable learning materials based on a student profile.

1.11.3 Algebra Performance

The algebra performance is the dependent variable that was used to measure the effectiveness of the treatments and the learning materials that were presented to the students for the basic algebra topic.

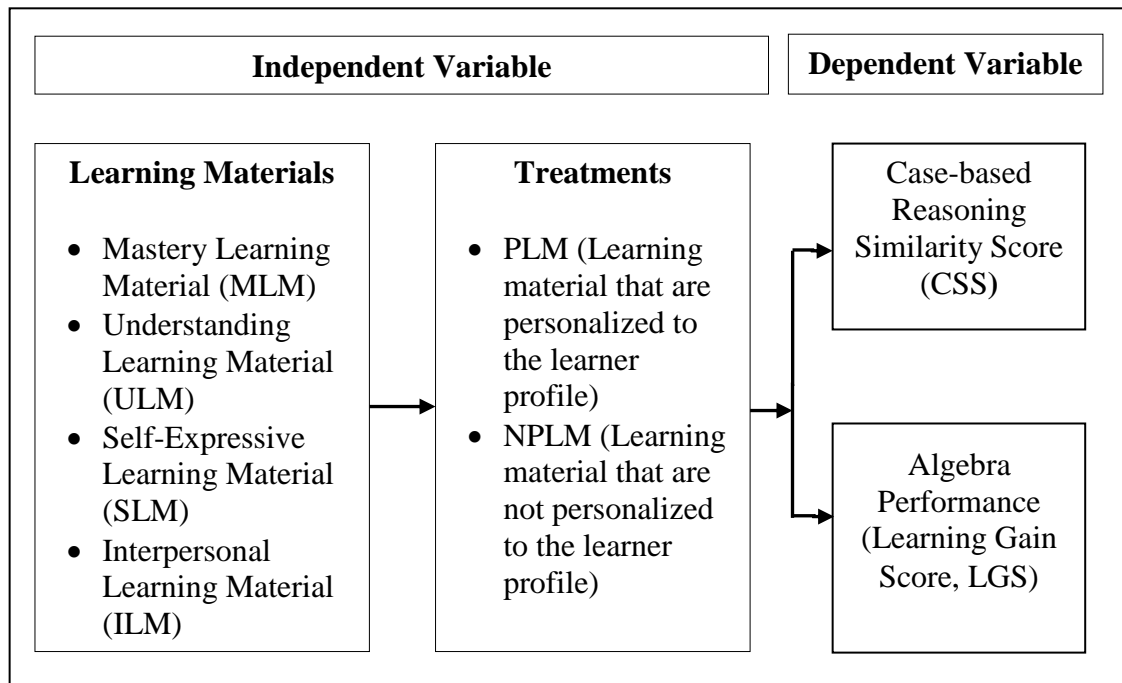


Figure 1.2. The Research Framework

1.12 Operational Definitions

The following operational definitions are to define and focus the terms related to the study.

Personalization

Personalized learning is an educational technique where the teaching and learning process is tailored to each student (Grant & Basye, 2014). In this study, the personalization technique is applied by mapping the student profile with the most suitable learning material.