



Durham E-Theses

Promoting Informal Learning Using a Context-Sensitive Recommendation Algorithm For a QRCode-based Visual Tagging System

COOK, HENRI

How to cite:

COOK, HENRI (2010) *Promoting Informal Learning Using a Context-Sensitive Recommendation Algorithm For a QRCode-based Visual Tagging System*, Durham theses, Durham University. Available at Durham E-Theses Online: <http://etheses.dur.ac.uk/463/>

Use policy

The full-text may be used and/or reproduced, and given to third parties in any format or medium, without prior permission or charge, for personal research or study, educational, or not-for-profit purposes provided that:

- a full bibliographic reference is made to the original source
- a [link](#) is made to the metadata record in Durham E-Theses
- the full-text is not changed in any way

The full-text must not be sold in any format or medium without the formal permission of the copyright holders.

Please consult the [full Durham E-Theses policy](#) for further details.

Academic Support Office, Durham University, University Office, Old Elvet, Durham DH1 3HP
e-mail: e-theses.admin@dur.ac.uk Tel: +44 0191 334 6107
<http://etheses.dur.ac.uk>



Durham
University

School of Engineering
and Computing Sciences

Promoting Informal Learning Using a Context-Sensitive Recommendation Algorithm For a QRCode-based Visual Tagging System

Henri Cook

A Thesis presented for the degree of
Master of Science

Technology Enhanced Learning Research Group
School of Engineering and Computing Sciences
University of Durham
England

March 2010

Promoting Informal Learning Using a Context-Sensitive Recommendation Algorithm For a QRCode-based Visual Tagging System

Henri Cook

Submitted for the degree of Master of Science (MSc.)

March 2010

Structured Abstract

Context: Previous work in the educational field has demonstrated that Informal Learning is an effective way to learn. Due to its casual nature it is often difficult for academic institutions to leverage this method of learning as part of a typical curriculum.

Aim: This study planned to determine whether Informal Learning could be encouraged amongst learners at Durham University using an object tagging system and a context-sensitive recommendation algorithm.

Method: This study creates a visual tagging system using a type of two-dimensional barcode called the QR Code and describes a tool designed to allow learners to use these ‘tags’ to learn about objects in a physical space. Information about objects features audio media as well as textual descriptions to make information appealing.

A collaboratively-filtered, user-based recommendation algorithm uses elements of a learner’s context, namely their university records, physical location and data on the activities of users *similar* to them to create a top- N ranked list of objects that they may find interesting. The tool is evaluated in a case study with thirty ($n=30$) participants taking part in a task in a public space within Durham University. The evaluation uses quantitative and qualitative data to make conclusions as to the use of the proposed tool for individuals who wish to learn informally.

Results: A majority of learners found learning about the objects around them

to be an interesting practice. The recommendation system fulfilled its purpose and learners indicated that they would travel a significant distance to view objects that were presented to them. The addition of audio clips to largely textual information did not serve to increase learner interest and the implementation of this part of the system is examined in detail. Additionally there was found to be no apparent correlation between prior computer usage and the ability to comprehend an informal learning tool such as the one described.

Conclusion: Context-sensitive, mobile tools are valuable for motivating Informal Learning. Interaction with tagged objects outside of the experimental setting indicates significant learner interest even from those individuals that did not participate in the study. Learners that did participate in the experiment gained a better understanding of the world around them than they would have without the tool and would use such software again in the future.

Declaration

The work in this thesis is based on research carried out at the Technology Enhanced Learning Research Group, the Department of Computer Science, University of Durham, England. Parts of this thesis have been accepted as part of:

- Cook, H., *Using QR Codes as a Means of Promoting Self-Driven, Informal Learning in Higher Education*, The Higher Education Academy: Information and Computer Sciences 10th Annual Conference (Poster Presentation), 2009

No part of this thesis has been submitted elsewhere for any other degree or qualification and all work contained herein is the work of the author unless referenced to the contrary.

Copyright © 2010 by Henri Cook.

“The copyright of this thesis rests with the author. No quotations from it should be published without the author’s prior written consent and information derived from it should be acknowledged”.

Acknowledgements

I would like to acknowledge several people, without the support of whom this thesis may never have existed. I owe a debt of thanks to:

My Family for their love, support and encouragement;

My Friends in Durham and later in London for their endurance and patience as each method, theory and result set was described to them time, time... and time again;

Researchers in The Technology Enhanced Learning Group at Durham University for creating a world-class research environment that never ceases to inspire, challenge and amaze;

To *Dr. Phyo Kyaw* and *Dr. Andrew Hatch* for proffering their considerable expertise and imagination in the completion of this project at the expense of their own valuable time;

And finally, to *Dr. Liz Burd* who provided me with the opportunity to complete an MSc. at Durham University. She can only be described as one of the most generous, intelligent and inspirational educators that I have ever encountered.

Contents

Abstract	ii
Declaration	iv
Acknowledgements	v
1 Introduction	1
1.1 Research Overview	1
1.2 Informal Learning with Designated Physical Objects	2
1.3 Recommendation Systems Based on User Context	3
1.4 Research Questions	4
1.5 Research Contributions	5
1.6 Thesis Outline	6
2 The Learning Process	8
2.1 Ways to Learn	8
2.1.1 Surface Approach	9
2.1.2 Deep Approach	10
2.1.3 Surface Learning Versus Deep Learning	10
2.1.4 Holists and Serialists	12
2.1.5 Strategic Learning	13
2.2 Engaging Learners	13
2.2.1 Passive Learning	13
2.2.2 Active Learning	13
2.3 Learning Theory	20

2.3.1	Types of Learning	20
2.4	Ways of Learning: Formal Versus Informal	23
2.4.1	Formal Learning	23
2.4.2	Informal Learning	24
2.5	Evaluating Learning	25
2.6	Chapter Summary	26
3	Learning Technologies	27
3.1	Introduction	27
3.2	The needs of Informal Learners	27
3.2.1	Information Quality	27
3.2.2	Mobile Interaction	28
3.2.3	Interconnectivity	28
3.2.4	Intelligence	30
3.3	Object Tagging	30
3.3.1	Introduction	30
3.3.2	Visual Tagging	32
3.3.3	Non-Visual Tagging	42
3.4	Recommendation Algorithms	46
3.4.1	Introduction	46
3.4.2	Collaborative-Filtering Based, Top-N Recommendation Algorithms	47
3.4.3	Chapter Summary	52
4	QRCode Tourist: A tool for exploring tagged objects effectively using context-sensitive recommendations	53
4.1	Introduction	53
4.1.1	Supporting the principles of Informal Learning	54
4.1.2	Provide a method of tagging and reading tags for arbitrary objects in a physical space	54
4.1.3	High Quality Information should be created for items	54
4.1.4	Learners should be able to rate items	55

4.1.5	Log Usage Statistics	55
4.1.6	Create a recommendation algorithm that aims to provide high-quality recommendations to learners	55
4.2	Platform	56
4.2.1	Hardware Device	57
4.3	A method of tagging and learning about objects	57
4.3.1	Tagging Objects	57
4.3.2	Learning About Objects	58
4.4	Creating information for objects	58
4.5	User Ratings	59
4.6	Logging Usage Statistics	59
4.7	Development Process	60
4.8	System Architecture	60
4.8.1	Component Diagram	60
4.9	Recommendations	61
4.10	Screenshots	63
4.11	Chapter Summary	63
5	Evaluating the QR Code Tourist Tool	64
5.1	Introduction	64
5.2	The Learning Task	65
5.3	Assessment of Learning Outcomes	67
5.3.1	Pre-Questionnaire	67
5.3.2	Post-Questionnaire	67
5.3.3	Focus Groups	69
5.3.4	Contextual Data	69
5.3.5	Ratings	70
5.3.6	Technical Measures	70
5.4	Participant Demographic	72
5.5	Limitations	72

6	Results and Discussion	73
6.1	Introduction	73
6.2	Participant Summary	73
6.2.1	By Gender and Discipline	73
6.2.2	By Degree Discipline	74
6.2.3	By Age	74
6.2.4	By Computing Ability	74
6.2.5	Prior Experience of a Visual Tagging System	75
6.2.6	Other Invariants	75
6.3	Summary of Questionnaire Results	75
6.3.1	General	75
6.3.2	Objects	77
6.3.3	Recommendations	78
6.3.4	Surroundings	79
6.3.5	Audio	79
6.3.6	Free-form Feedback	80
6.4	Summary of Results from Technical Measures	82
6.4.1	Click-through	82
6.4.2	Object Views and Scan Failures	83
6.4.3	Distance Between Tags Scanned	84
6.4.4	Audio Clip Clicks	84
6.5	Object Information Page View Summary	84
6.6	Recommendation Usage	85
6.7	Detailed Analysis	86
6.7.1	Prior Computer Experience Versus Perceived Benefit	86
6.8	The Study In Perspective	87
6.8.1	Evaluation Methods	87
6.8.2	Focus Group	88
6.9	Chapter Summary	89
7	Conclusion	90
7.1	Introduction	90

7.2	Thesis Summary	90
7.2.1	Are learners interested in the objects around them in a typical educational space?	91
7.2.2	Does prior computer usage affect the benefit a learner believes they have gained from learning informally using a mobile, electronic device?	91
7.2.3	Does the addition of audio clips to primarily textual, on-screen information make it more interesting to learners?	92
7.2.4	Based on information about a learner and objects that the learner has recently been searching for information on, can an algorithm predict other objects that the learner might be interested in?	92
7.2.5	Do learners respond positively to informal learning using mobile devices by highlighting that they would travel a large distance to see more, or allow learning about designated objects to influence their schedule?	93
7.3	Future Work	93
7.3.1	Informality of Experimentation	93
7.3.2	Variety and Availability of Tagged Items	94
7.3.3	Quality of Information	94
7.3.4	Interconnectivity	94
7.3.5	Improved Tagging System	95
7.3.6	Comparison Versus Model-Based Recommendation Algorithms	95
7.3.7	Interacting with Mobile Devices	96
7.4	Conclusion	96
	Appendix	98
A	Case Study Materials	98
A.1	Graphical Instructions	98
A.2	Written Instructions	100
A.3	Learning Materials for the Task	102

A.4	Consent Form	108
A.5	Pre-Questionnaire	110
A.6	Post-Questionnaire	112

List of Figures

3.1	In a simple example of EMC the chain of communication would resemble this. [38]	32
3.2	A QRCode example	34
3.3	A Data Matrix example	35
3.4	A ColorCode example	37
3.5	A Shotcode example	38
3.6	Mean First Read Rate (FRR) percentage for each 2D barcode in different data quantities, symbol sizes, and camera resolution. [53]	40
3.7	A summary of results obtained by Kato and Tan [53] Some of the codes mentioned are not being reviewed.	41
4.1	The HTC Touch 3G	57
4.2	A diagram of the components that make up the QRCode Tourist Tool	60
6.1	Participant Discipline Distribution	76
6.2	Prior Experience of using a Visual Tagging System Amongst Participants	76
6.3	Information Views By Participant	83
6.4	Participants rating the informativeness of the information provided by Prior Computing Experience Level	87

List of Tables

3.1	“Storage capacity for Data Matrix codes of various sizes” [99]	36
4.1	A subjective comparison of various mobile platforms as of December 2008. All scores are out of five unless indicated otherwise	57
4.2	A list of the variables involved in the computation performed by the QRCode Tourist Tool’s Recommendation Algorithm.	61
6.1	Participant answers regarding computing activities.	74
6.2	Distribution of responses to the ‘General’ section of the post-task questionnaire	75
6.3	Distribution of responses to the ‘Objects’ section of the post-task questionnaire	77
6.4	Distribution of responses to the ‘Recommendations’ section of the post-task questionnaire	78
6.5	Distribution of responses to the ‘Travelling for Recommendations’ section of the post-task questionnaire	79
6.6	Distribution of responses to the ‘Surroundings’ section of the post-task questionnaire	79
6.7	Distribution of responses to the ‘Audio’ section of the post-task questionnaire	80
6.8	Summary of Results from Other Technical Measures	82
6.9	Summary of Information Page Views, By Object Title	85
6.10	Distribution of Information Page Views: Recommendations Versus Scanned Tags	85
6.11	Recommendations selected by users, By Position Displayed in the Tool	86

Chapter 1

Introduction

1.1 Research Overview

In recent years the internet has become increasingly prominent on mobile devices offering users access to connected services at any time from anywhere with wireless service coverage. This advent has seen a vast increase in mobile applications for a variety of uses, including learning. Mobile learning is often informal - casual lookups of pieces of information that supplement or expand upon an existing model in the learner's mind. Resources for learning specifically in this way are few and far between. Harnessing the educational potential of this relatively new medium can provide positive benefits. The mobile platform offers new ways to present, organise, integrate and monitor learning information. Mobile telephones in particular are very personal devices and are becoming increasingly integrated with web services like Twitter, Facebook and Google Mail - harvesting this information and using it to address a learner's specific needs can create a substantially more meaningful experience than current, more generic technology such as web search engines.

In contrast to traditional, more formal and often paper based methods of learning such as academic papers or lecture materials web-based content can be highly connected to other reference sources that serve to augment the material that a learner is viewing and, while not seeking to replace teaching's more staple formal presence, help the learner to create links and understandings that previously would have involved interaction in a more formal environment (such as a professor's office

or lecture theatre).

Informal Learning can occur anywhere, at any time and it is important that a technological solution supports this. The purpose of this thesis is to present one such method of enabling Informal Learning. Moreover this paper seeks to augment the learning experience, using recommendations based on information that can be gleaned about the user through interconnectivity with data maintained by other services (such as academic institutions).

1.2 Informal Learning with Designated Physical Objects

Maslow [28] describes the ideal college, a place in which “there would be no credits, no degrees and no required courses... A person would learn what he wanted to learn”. While this does not further the goals of the current educational system, with its relatively rigid subject boundaries, it can be seen as a goal strongly supported by the notion of completely Informal Learning. Students can take the time to learn about anything that interests them, something they see, read or hear about in a completely *self-directed* fashion. This has become even easier with the evolution of the World Wide Web, fast and near-ubiquitously available access to information on an enormous variety of subjects means that there is an excellent chance of learners being able to access what they want, when they want it.

Informal Learning can be defined as a learner exploring that which is around them in a self-directed fashion (i.e. no external instruction or intervention beyond providing appropriate tools). Other definitions such as those found in [10] also include “learning from family members” as well as any learning taking place outside of a ‘controlled educational context’ such as “museums, galleries, science centers, parks, and zoos”. This thesis’ definition accepts that Informal Learning can happen anywhere at any time and does not necessarily have to involve technology, although this is the focus of its inquiry. Cross [20] refers to the places that informal learning occurs (i.e. outside of the classroom) as *Learnsapes* which is terminology this paper adopts when describing physical areas containing items of intellectual interest

(Designated Physical Objects, or DPOs).

The biggest problems encountered in the world of informal learning are common across the entire educational field: information provision [51], motivation [62] and regulation [10]. Learners should ideally be motivated to access the information around them, which must be accurate and up to date and educators need a way to regulate that learning which at the most basic level, would simply ensure that learning was indeed occurring.

This Thesis aims to propose and evaluate potential solutions for these problems by utilising common mobile, wireless technology.

1.3 Recommendation Systems Based on User Context

Recommender Systems “allow people to find the resources they need by making use of the experiences and opinions of their nearest neighbours” [67] the most well known of such systems in recent years has been the system in use by *Amazon.com* where recommendations are based on one’s individual purchase patterns. Individual purchase patterns are compared to the patterns of other customers to create a likelihood that a user will be interested in a different product. Obviously as with many recommendation systems of this nature the larger the corpus of available purchase data the more accurate subsequent recommendations will become, and gathering a suitable corpus is often one of the biggest challenges when creating recommendation systems that rely entirely on this method of “collaborative filtering” [45].

Collaborative filtering algorithms are one of the most successful recommenders and provide significant advantages over earlier methods of filtering/recommendation [45] such as:

- **Keyword filtering** Returning applicable items using a simple search for words they contain. This method was used in many early internet search engines and to a degree is still in use today. On its own however keyword filtering often returns too many results to be accurately assessed by a user,

which limits its usefulness as a (criteria-based) recommendation method.

- **Human-based classification or selection** Like many human-driven methods of classification, this can be prone to bias or misinterpretation and unsustainable scaling. Collaborative filtering, involving the users in the classification process, is essentially an expansion of Human Classification but with participants only mildly, if at all, aware that they are taking part in the process (and hence produces very realistic results).

One of the most common problems encountered when employing user-based collaborative filtering algorithms is one of efficiency, as computational complexity grows with the number of participants. It is for this reason that “model-based recommendation techniques” [22] have been developed which calculate the similarity between various items, based on data such as the “user-item matrix” [22] - these calculations offer significant efficiency advantages over previous, user-centric approaches.

This Thesis utilises a model-based item recommendation algorithm to recommend physical learning objects to learners. This algorithm, augmented with additional heuristics forms the basis of an investigation into whether or not meaningful recommendations can be created in an Informal Learning Case-Study.

1.4 Research Questions

This thesis presents an Empirical work that is geared towards answering the following Research Questions:

- R1 Are learners interested in the objects around them in a typical educational space?
- R2 Does prior computer usage affect the benefit a learner believes they have gained from learning informally using a mobile, electronic device?
- R3 Does the addition of audio clips to primarily textual, on-screen information make it more interesting to learners?

R4 Based on information about a learner and objects that the learner has recently been searching for information on, can an algorithm predict other objects that the learner might be interested in?

R5 Do learners respond positively to informal learning using mobile devices by highlighting that they would travel a large distance to see more, or allow learning about designated objects to influence their schedule?

Within these questions a ‘typical educational space’ can be defined as “a location within an institution (be that a university, college or school) that contains educational objects,” these are most commonly posters on specific or wide varieties of subjects adhered to walls as well as other display artefacts (e.g. sculptures, portraits) that one may typically expect to find in a public area.

1.5 Research Contributions

In the pursuit of potential answers for the Research Questions this work will contribute the following:

- **A tool for exploring a physical environment containing ‘tagged’ learning objects.** The ‘QRCode Tourist’ tool will enable learners to discover new information about the objects around them in an Informal and Constructivist manner. The tool contributes the ability to:
 - *Gain dynamic information about objects in a physical space.* Informal learning is by its very nature unstructured, learners are required to have access to a wide range of objects to satisfy this detail. The object scanning experience is completely user-driven and as a result it must be obvious which items have information attached, and how the learner can go about accessing that information.
 - *Present object information that is augmented to aid understanding.* Capitalising on more recently prominent learning methods such as the use of audio clips and videos in object information retains learner attention, providing variety to the experience.

– *Display recommendations in an appropriately accessible manner.* The tool takes recommendations generated by the recommendation algorithm and presents them in a way that is accessible to learners to aid knowledge acquisition.

- **An algorithm to produce recommendations that are interesting/applicable to the learner using elements of user context.** Informal learning, while unstructured, can still be motivated and targetted. Reviewing information for new objects - especially in an unfamiliar subject area - can often lack direction. While too much direction creates a structure that detracts from the informality of the experience, optional features such as recommendations or 'suggested viewing' can serve to augment.

1.6 Thesis Outline

The structure of the thesis is as follows:

Chapter 2 describes the wider literature in the field of education. It pays special attention to many of the traditional methods of formal learning and describes the informal alternatives that can supplement or replace them. It also presents the various ways in which we as learners acquire knowledge and how best this knowledge can be retained, and propagated. Expanding upon this base the chapter also seeks to address the deficiencies of current methods and potential improvements that could be made to them.

Chapter 3 presents a review of the technical literature encompassing the technologies that could be applied in the face of the research questions (Section 1.4). It highlights methods of attracting attention to objects of interest in a physical learning space as well as discussing how learning information can be maintained and transmitted to learners in a sustainable, and highly available fashion. The web as a learning tool is also discussed before going on to detail different kinds of algorithms for providing recommendations and assessing the best kind to be used in this thesis.

Chapter 4 elucidates the 'QRCode Tourist' Tool, a tool that allows learners to glean information about objects in a physical learning space and recommend other

objects that they may be interested in based on factors such as context, and previous object interaction.

Chapter 5 discusses the design of an experiment to investigate the proposed research questions involving learners in a real-world setting, using various aspects of the information that can be accessed about them (their *context*) to provide targeted recommendations and learning information through the *QRCode Tourist* tool.

In Chapter 6 the effectiveness and results of the techniques that are proposed for promoting and enabling Informal Learning are evaluated. Each outcome is referenced to an appropriate research question and is accompanied by a thorough discussion of the contribution that can be inferred from the evidence gathered.

Finally, Chapter 7 summarises the conclusions we can draw from the work presented in this thesis and suggests future work that could further the study and practice of learning in this field.

Chapter 2

The Learning Process

“The array of things learned is so vast that we ought not to expect any simple theory of learning to suffice. No problem in psychology has inspired so much experimental research as learning. Yet if we were to criticize the output to date we should say that current theories tend to be one-sided and narrow. They lack the sweep required to embrace the many forms of learning that occur.” *G.W. Allport (1964)* [2].

2.1 Ways to Learn

In 1976 Marton and Saljo [66] performed an experiment that subjected two groups of students to what can be effectively described as a comprehension test. Students were given a document and told they would be tested on their understanding of it afterwards. From the result the authors produced two definitions of the approaches that the students used to comprehend the documents provided and an analysis of how effective these approaches were based on performance in the final test. This work by the duo is often cited as “seminal” when considering the research on various approaches to learning that has occurred since their paper was first published. [15]

A vast amount of literature focuses on ‘an education’ in the modern world being little more than facts and formulae that students have memorised without any gain in intelligence or *knowledge* [65, pp. 25]. This is often blamed on the need for the educational system to be assessed, and assessable. Goals must be set and completely freeform or partially structured learning is difficult in such a situation - there must

be milestones and benchmarks for students to reach in a relatively transparent fashion. Research into learning has focused on this trait - students ability to reproduce information that they are given (such as in the Marton and Saljo [65] study) rather than focusing on learning in *qualitative* terms. Early research by Bartlett [5] lead him away from the belief that memory functioned as merely a “reproductive storage mechanism” [5, pp. 84-85] and instead it depended upon schemata; constructs of meaning that represent personal interpretations of material - his thoughts traveling in the same direction as what eventually became publicised by Piaget [84] as *Constructivism*.

2.1.1 Surface Approach

Students employing the “Surface Approach” or *Surface Learners* “skated along the surface of the text” [66] remembering only a “list of disjointed facts” later. This approach involved learning the minimum amount required to progress in their situation. Surface Learning is often described as a type of learning that can be likened to “rote memorization” [32] or “cutting corners” [8]. Additionally, work by Franson [37] indicates that students who feel threatened while learning are less likely to learn effectively and employ a “Surface Approach” which results in lower retention. Length of the overall interaction is important with shorter interactions (short time constraints) more commonly being associated with Surface learning [65].

Students who utilise a Surface approach often concentrate on the final goals, without considering the material they have been presented with in any great detail. In the Marton Study [65] (further described by Entwistle [28]) ‘surface students’ would make statements such as: “I didn’t remember what I read, because I was just thinking of hurrying on” or “The whole time I was thinking ‘now I must remember this’” [28].

Other studies in areas related to Surface Learning include Goldman’s 1972 study [40] in which one group of candidates tried to learn “the underlying reasons for [a] technique in a verbal way” and another tried to “learn the computation technique by observing examples, often without worrying about reasons for the technique.” The latter strategy described is known as the *Mnemonic-concrete Strategy*, surface

learning, or learning by rote.

2.1.2 Deep Approach

Deep learners are significantly more involved with the subject matter, often performing large amounts of background reading and research to further their understanding in a genuinely enthusiastic manner. In the Marton and Saljo [66] study this meant that those comprehending “saw the big picture and how the facts and details made the author’s case”. This type of learning usually results in a comparatively “better recall of detail, particularly after a five-week interval” [32]. Students attempting a ‘Deep Approach’ can conceivably “fail to reach a deep level of understanding through lack of previous knowledge” [32] whereas in contrast students attempting a surface approach are highly unlikely to ever reach a deep level of understanding without a conscious change of mental direction. Achieving a deep approach, from an educator’s perspective is about engaging the student and helping them to facilitate their own learning.

Students who attain a deep approach are usually concerned primarily with the material to hand, in the Marton study these students were identified using the following keywords to describe their thought process during the experiment: “thought about”, “got a grasp of”, “tried to get at”, “the point of it”, “what it was about”, “the conclusions” [28, pp. 128-129].

2.1.3 Surface Learning Versus Deep Learning

Early work by Marton [28, pp. 133] notes that some Arts students are ‘reproductive’ - giving back “prescribed [learning] material intact” and others are “transformational, [ranging] widely over the material and [injecting their] own meaning and interpretations”. Biggs’ [8] later work goes on to classify these traits further into “surface” and “deep” learning methods. He emphasises the fact that both Surface and Deep methods are merely ways to approach a particular task and are not necessarily characteristics of the student. Each kind of learning approach can be applied to different contexts without being entirely context-based. Some students for example may have

a preference for a particular type of approach when entering a situation which will affect their final performance. These predilections can be assessed using questionnaires such as Entwistle and Ramsden's *Approaches to Study Inventory* (ASI) [30] and Biggs' *Study Process Questionnaire* (SPQ) [9] with results being affected by the environment in which they learn. Students often "adapt to the expected requirements" and the resulting metrics of these questionnaires can be used to evaluate the teaching environment in question.

Marton [28, pp. 130] describes Surface and Deep Learning as distinct learning strategies with the Deep Approach being more successful in terms of those who employed it being able to fully grasp the provided text. The various approaches he summarised as "learning is learning through the discourse" (Deep) and "learning is learning the discourse" [28, pp.130] (Surface). Deep learning students have a higher "level of processing" and hence a better "level of outcome" [28, pp.132].

Biggs [8] goes on to conclude that learning, as a way of interacting with the world, is about "conceptual change" - the process of applying what you see to what you already know and forming new ideas and concepts from the experience. This is assisted greatly by certain criteria namely: clear expression of goals, motivation (students need to want to achieve), lack of time constraints (being free to focus on the task) and being allowed to work collaboratively "in dialogue" with others. Biggs states that "Good Dialogue elicits those activities that shape, elaborate and deepen understanding" [8].

Biggs concludes that the "low cognitive level of engagement" associated with the surface approach "yields fragmented outcomes that do not convey the meaning intended by the encounter" and that the deep approach is "more likely to help the student construe the meaning" [8]. As a result he asserts that the surface approach is "to be discouraged" and "the deep approach encouraged" as part of a good teaching method. In a potentially field-changing piece of recent work Marton & Booth [64] explore the "apparent paradox of the Asian Learner" [64, pp. 39] who appears to rely on rote memorisation and also manages to take a deep approach to understanding. Further examination reveals a unique cultural distinction between "memorizing with intention to understand" and "mechanical memorization" [64,

pp. 39] in these students creating a 'deep-surface' hybrid approach that produces results that are the same, if not better than either alone explaining how they would "do so well in competition with their western counterparts" [64, pp. 39].

The much-cited work by Entwistle and Ramsden [32] proves in a relatively small study (n=30) that deep learning is the most effective type of learning for good examination performance.

2.1.4 Holists and Serialists

Holists look at the whole breadth of a subject area and seek to interconnect the topic they are learning about with other topics while creating their own "personal and idiosyncratic analogies" to aid with understanding [26]. A more detailed analysis of the structure created and the available evidence to support it will typically come later in the learning review process with the Holist being "likely to put off what he may see as the more boring parts of learning" [26]. Pask [80] describes the process of a Holist learner being hasty in their creation of models and analogies as "globetrotting" - the constructs that result from this process can often be misleading or inappropriate.

Serialists or 'Atomists' "fall into the opposite trap" to Holists [26] - they often miss "important analogies" and struggle to relate individual topics to the subject area as a whole. Pask [80] calls this pathology "improvidence".

Daniel's [28, pp. 84-86] initial work says that Serialists will typically "teach [a] subject back in exactly the same order they had learnt it [in]" whereas Holists, with their overall view of the subject matter will teach back in a "coherent manner [with] major changes in the order of presentation". This is confirmed in earlier work by Pask [81] where he makes the distinction between those who "learn, remember and recapitulate a body of information in terms of string-like cognitive structures where items are related by simple 'data-links'" and those who "learn, remember and recapitulate as a whole" [81].

2.1.5 Strategic Learning

Entwistle [32] proposes the idea of a strategic learner - a hybrid Surface/Deep learner that seeks “to achieve the highest possible grades” [65].

Intention is touched on briefly in work by Ausubel et al. [4, pp. 41] who state that if the learner’s goal is to memorize material by rote rather than understand meaningfully “neither the process nor the outcome of the learning can possibly be meaningful” - assuming a learning outcome that is not rote. In the same work Ausubel et al. [4] also discusses students who employ a ‘learn by rote’ strategy because they have found from “sad experience that substantively correct answers lacking in verbatim correspondence to what they have been taught receive no credit whatsoever from certain teachers” [4, pp. 42].

2.2 Engaging Learners

2.2.1 Passive Learning

Marton’s account of his experiments in surface and deep learning [28] describe surface learning as being caused by a “passive approach”, i.e. not taking an active interest in the material provided. Students taking part in his experiment made statements such as “It was words ... you didn’t have to think about what they meant, it was just a matter of reading straight through” and “... that I read it sort of because I was supposed to read it ... and not so as to react to it”. This can be claimed to be a result of the laboratory situation, students being told to read a text without any instruction to understand it - but this is comparable to the structure of a typical course of instruction in a learning institution, with some similar results from students as the participants observed by Marton [28, pp. 130]

2.2.2 Active Learning

“Good teaching is getting most students to use the higher cognitive level processes that the more academic students use spontaneously” *J. Biggs* [8]

Active learning describes a type of education that involves participation. Students are expected to actively engage and interact with the material that they are trying to comprehend.

Rogers [88] describes *experiential learning*, a “self-initiated” or *self-directed* form of learning [88, pp. 5] that is already pervasive in modern society throughout both child and adult life. Many children for example learn not to touch hot objects by experiencing what it is like to touch one themselves, first hand, and the resulting negative effects. This is in contrast to someone else describing the experience of what happens when touching a hot object to the child which can often lead to a less satisfactory result/level of retention. Many members of society choose to pursue sports or hobbies that involve educating themselves before attempting to take part. Such learning is “evaluated by the learner. He knows whether it is meeting his need, whether it leads toward what he *wants* to know, whether it illuminates the dark area of ignorance he is experiencing”. Such self-gleaned knowledge, as opposed to being taught by someone where the instruction is based upon their own perspectives and mental constructs embeds itself in a way that the learner “will not soon forget” [88, pp. 4].

Rogers [88] explores other applications of self-directed learning such as those used by “Dr. Volney Faw, of Lewis and Clark College” [88, pp. 30-52] in a relatively free form course where students assist in setting the schedule, managing their own curriculum and even running numerous “student-centric” sessions to enumerate findings from their research. Rogers [88] discusses the “creative problem solving” this type of approach engenders, primarily targetted at the more “rigid educational limits” of the secondary and college/university levels of the education system. Encouraging creativity in an engaging fashion such as this leads to a “tremendous release of productivity and creativity in students” and is compared positively to the more traditional “mug and jug” approach whereby students are the mug and the lecturer the jug ‘filling’ them with knowledge. Those students who reproduce the exact concoction that is ‘poured’ into them excel whereas others who do not recite the correct information, but rather some variant of it, suffer [88, pp. 35].

Throughout much of the literature on both the passive and active approaches to learning is an emphasis on the student being perceived as more than a “passive recipient of information ... a bundle of stimulus-response connections”. Rather, he should be “regarded as an active participant in the knowledge-getting process, one who selects and transforms information, who constructs hypotheses and who alters those hypotheses in the face of inconsistent or discrepant evidence” [28, pp. 105]. Bruner [28] goes on to recommend the use of the “enquiry method” in teaching, promoting active “discovery” and seeking of facts. He believes this should encourage more imaginative, yet challenging ways of thinking that will allow more students to “go beyond the information given” [28, pp. 106].

Promoting Learning - Motivation and Attention

Stipek [100] describes motivation as “an active process requiring conscious and deliberate activity” and states that it is important for educators to “provide a learning context in which students are motivated to engage actively and productively in learning activities” - attention being described as an effect of Motivation.

Entwistle [26] extrapolates two different types of motivation from original work by Peters [83]: *extrinsic* and *intrinsic*. The former refers to a task that once accomplished gains some kind of non-task based reward - such as a cash prize for doing well in an examination or an elevation of social status for achieving a goal. Intrinsic motivation “depends on seeing the task as relevant and interesting in its own right” [26]. Wilson [109] states that “inner needs” such as a “need for achievement” or the desire to have higher self-esteem can also be described as goals applicable to intrinsic motivation and this is adapted by Entwistle in his later work with colleagues [65]. Stipek [100] describes something similar in her description of “Achievement Motivation” where subjects simply crave achievement for a variety of reasons from recognition to not looking ‘dumb’ in front of their classmates and this closely parallels Covington’s proposal of “self-worth” motivation [19].

White [107] introduces the idea of “competence motivation” or “effectance motivation” whereby a subject may be motivated to produce an effect merely by their own efficacy as a result of learning by rote, the results of coincidental actions or

learning by trial and error. Allport [2] discusses the concept of *imprinting* from the perspective of the nervous system (or ‘unconscious self’) whereby a positive sensation associated with an action - such as a feeling of exhilaration on accomplishing a goal - can create a bond between action and result along with a desire to engage in the action again for the same good feeling. The opposite is also true and negative experiences can lead to a ‘negative association’ which impacts future activity. This can be demonstrated by the popular example of a child learning not to touch an open flame - while more drastic than a negative learning experience the end result is similar. Whereas a flame experience will likely prevent further attempts after one or two occurrences, a setback in a learning context would not necessarily stop further attempts immediately but after many minor occurrences of this kind the result will ultimately be the same.

Recent psychological work on “seeking behaviour” strongly reinforces the idea of competence/effectance motivation or “Appetitive Motivation” - the need to learn and discover new things simply because it’s possible. The subsequent reward of acquiring new knowledge, mastering a new task or “pursu[ing] the fruits of [our] environment” is enough to award us a Dopamine (DA) boost from the “Seeking System” [79] of the Brain which encourages such behaviour in the future - the authors theorise that all human strivings are “ultimately driven” by this system [79] and cite modern technological devices such as mobile phones as exacerbating this trend by putting facts and figures at a learner’s doorstep. This technological availability and innate human desire to discover new facts that interest them creates a natural Informal learning network.

Especially important in encouraging efficient learning is the idea of *Positive Reinforcement* which Marton et al. [65] describe as “behaviour which leads to satisfying effects”. Students who receive immediate feedback (such as knowledge of results allowing them to improve) from their work are more likely to repeat the behaviour in the future. This sort of mantra is based on an ‘age-old’ principle of reward and punishment as demonstrated for the first time empirically in Pigeons by Ferster and Skinner [35]. This method of learning is now being used in a variety of fields such as teaching children with learning and social difficulties [34]. Marton et al. [65] go

on to describe the body of opposition to this kind of “programmed learning” being effective in the classroom and the view of a teacher as a “manipulator of learning” being incorrect. Stipek [100] describes positive reinforcement as an example of “traditional reinforcement theory” and describes how it is often viewed as “mechanistic” as it fails to take into account people’s “beliefs, feelings, aspirations or any other psychological variable[s] that cannot be observed directly” [100].

Reinforcement theory encourages a behaviour-based approach to motivation, Stipek [100, pp. 10–11] describes how a Reinforcement Theorist would first observe a subject’s behaviour, determining which actions are detrimental to his learning performance and then introduce a system where these behaviours were “punished, or at least not rewarded” and the positive behaviours rewarded. The idea of *Cognitive Motivation* originated in the 1960s and was largely concerned with adding a psychological spin to this “mechanistic” theory of reinforcement. Stipek’s example takes a student who works hard because they believe (psychologically) that their efforts will be rewarded in the future, rather than basing their reasons for performing the task at hand on historical evidence of reward.

Cognitive Theorists are “also interested in the mediating effects of other beliefs associated with expectations - such as perceptions of one’s ability, perceptions of one’s control over achievement outcomes, and perceptions of the causes of achievement outcomes” [100, pp. 11] and their actions when trying to improve motivation would likely focus at “changing maladaptive beliefs” such as alleged lack of ability.

Encompassing a large amount of these theories is the idea of *Goal Theory* whereby students’ goals are considered important to correcting maladaptive practices [100, pp. 13]. If a student’s goal is to achieve a certain minimum grade, their motivation will likely lack after this level has been attained. Similarly if students would rather enjoy themselves than work, their learning will not be as effective as it would have been if they committed to an achievement goal. Goal Theorists would attempt to change student’s goals to correct “maladaptive behaviours” [100, pp. 13]. For Reinforcement Theorists “changes in a person’s behaviour [with respect to Achievement Motivation] are produced by changing contingencies in the environment” [100, pp. 13] whereas the other perspectives take a more experiential approach, exploring

the subject's mindset and the past experiences that shaped it before assessing any potential negative impact of the surrounding environment.

Self-confidence is vitally important for effective learning. Entwistle [26] uses earlier research [31] to discuss the concept of students who study due to "fear of failure" and whether or not this affects their ability to perform in a learning environment, he identifies empirical evidence from Coopersmith [18] who showed that children with more belief in their abilities than their co-learners performed better in terms of "success experiences". This can be connected with the idea of "competence motivation" - people enjoy doing tasks at which they are proficient and the more proficient tasks that an individual can add to their repertoire the more satisfied and willing to learn they will be. Along the same line of reasoning it is also fair to consider the effects of "incompetence demotivation or having no achievable or satisfying goal in learning" [65] which relates back to Entwistle's concept of "fear of failure" [26].

Rogers [88] asserts that the "problem with learning today" is that it is hampered by the competition the current system engenders, with students competing against each other for achievement. This sort of strategy "crush[es] both curiosity and self-confidence" [88] and he puts forward that a new approach to learning, where emotion is considered important as a "significant, existential" approach to learning that "develops personality as well as the intellect" [65].

Marton et al. [65] describe how easy it is to attribute blame for lack of motivation or attention to the student, rather than examining the underlying causes. They take a quote from a lecturer concerning a student's lack of achievement:

"The main trouble is unwillingness to get down to work, but having said this, there is no doubt a paradox... in that at some time in the past, in order for a person to have got here, presumably he had been willing, and something is going on which diminishes this willingness." [65]

The lecturer sees the change in the student but is completely puzzled about the change in attitude from the student, a reversal of the perspectives in Entwistle's [28] experience with surface and deep learners.

Understanding

Biggs [8] discusses in some depth the concept of *understanding* and how once a student attains this level of knowledge it is hard, if not impossible, to lose again (people don't lose a true understanding). Students interviewed in his study described understanding as a "satisfying" and "complete" experience which they attain by truly taking part in a subject.

Provoking Critical Thinking amongst students is identified by Marton et al. [65] as an important goal in University (Higher) teaching, the authors summarise findings by Entwistle & Percy [29] that sample lecturers at various institutions and determine that the existing system of lectures, tutorials, practical classes and seminars does not appear to be attaining this goal and the methods to make it more achievable are unclear. Importantly from an examination of assessments and methods of teaching it "seemed that lecturers looked for critical thinking, yet taught and assessed conformity in ideas and the acquisition of detailed factual knowledge" [29]. Why this disparity between what teachers hope to achieve and what they actually achieve exists is often attributed to "indolent" students or those who simply "don't understand" but not all lecturers accept this point of view determining that there must be something "going on which diminishes [the student's] willingness".

It is very easy for students to establish a 'personal understanding' of a subject based on their own life experiences and the "essential uniqueness of each person's cognitive structure" [4]. The basis for learning a subject is often constructed from only a partially shared set of experiences and knowledge. Ausubel et al. [4] discuss the resulting necessary "construction of meaning". Entwistle [65] describes this process, "New information has to be interpreted in terms of prior knowledge and concepts which contain shared, and unique, shades of meaning. What a student learns can therefore be exactly what is taught only in relation to facts or formally defined concepts".

Collaboration

Collaborative learning has been shown to benefit all members of a project, rather than just those who enter the experience as 'less knowledgeable'. The process of

explaining a problem benefits the explainer as well as the target of the explanation [23]. Those who understand benefit as they explain and defend their own knowledge and those who do not benefit from the explanation, John and Wheeler [52] describe this method of learning as a type of “reciprocal scaffolding”. This ‘Scaffolding’ is a teaching structure that sees an expert start in a very supportive fashion and slowly taper that support away until the least expert members of the group are functioning virtually independently.

The principles demonstrated in Collaborative Exercises can also be applied to the teaching experience, subject’s need not be collaborating with another student but could be interacting with an expert in a semi-structured fashion. This method may be useful in teaching new techniques or tools and is often found in laboratories and classrooms in the form of demonstrating members of staff acting as an expert in the “Scaffolding” model [52].

2.3 Learning Theory

2.3.1 Types of Learning

According to Biggs [8] various “theories of teaching and learning focusing on student activity are based on two main theories: phenomenography and constructivism”. The former was a term coined by Marton [63] to describe the theory that grew out of his original studies with Saljo [66] while the latter “has a long history in cognitive psychology” [8] and today takes “several forms: individualism social, cognitive and post-modern” [8].

Phenomenography

Phenomenography explores the way that students understand what they learn or their “structures of awareness” [65] and originates from the well-known experiment by Marton & Saljo [66] described previously. Entwistle [27] says that “while this initial study itself cannot be strictly described as phenomenographic it certainly developed the techniques of rigorous qualitative analysis which have become one of the hallmarks of phenomenography” namely it is the process of self-reflection that

Marton & Saljo [66] engage in afterwards; examining the underlying meaning of the different categories they identify which hints at a phenomenographic process. Phenomenography then can be described as the process of inferring categories from a set of results and examining the relationship(s) between them for meaning or, as described by McKeachie [65, pp. i-iv], Phenomenography is “a sort of hard nosed phenomenology in which intensive interviews of learners are systematically collected and analyzed. These may be followed by experiments testing the understanding gained from interviews.” [65]

Entwistle [27] mentions that Phenomenography, as an approach, is often challenged because of the subjectivity involved in establishing “categories of description” - largely on the grounds of theoretical purity - the true test for higher education researchers however is whether or not the process produces valuable insights into teaching and learning. Indeed, the process of conceptualising various methods of learning is very applicable to teaching and learning; the reflection aspect combined with the critical process of evaluating the meaning behind a participant’s response encourages the right approach to the various problems with which students are presented as part of their education.

Entwistle describes the challenges new researchers in the Phenomenographic field face namely a “lack of precise descriptions of what is necessarily involved with phenomenography” stemming from initial research papers not explaining the more practical aspects of their procedures effectively. As a result “the path from interviews through inference to categories can be difficult to follow, leaving the findings unconvincing” [27] and researchers find it hard to effectively utilise the “crucial strengths of the approach”.

Constructivism

Constructivism “has come to serve as an umbrella term for a wide diversity of views” [24]. In the context of *how* we learn it applies to the process of building (or constructing) knowledge. Importantly this contrasts the idea of the learner simply receiving knowledge imparted from others as if they were a vessel to be filled and emphasises understanding and reading around a subject outside of their formal

education environment. Duffy and Cunningham [24] describe how constructivists view the learning activity holistically and in context, rather than using educational content as their only source of reference for how learning occurs. “[An individual’s] situation as a whole must be examined and understood in order to understand the learning”, “The entire gestalt is integral to what is learned” [24].

A cornerstone of Constructivism is that everyone remembers and understands differently because everyone has seen and experienced different events in life. As a result people draw unique relations between facts when learning. The individual ‘structure of understanding’ that is the result of this process will be unique to an individual and is by its very nature hard to predict by empirical process [24]. Perkins [82, pp. 49] offers an excellent summary of this, “Central to the vision of constructivism is the notion of the organism as ‘active’ - not just responding to stimuli, as in the behaviourist rubric, but engaging, grappling, and seeking to make sense of things. In particular learners do not just take in and store up given information. They make tentative interpretations of experience and go on to elaborate and test those interpretations.”

Duffy and Cunningham [24] go on to discuss criticisms of Constructivism, which often focus on this unique attribute and the implication that “constructivism leads inevitably to subjectivism” quoting an established Constructivist, Bruner: “How does this view affect my view of the world or my commitments to it, surely does not lead to ‘anything goes.’ It may lead to an unpacking of suppositions, the better to explore one’s commitments” [12]. Bruner discusses another criticism, namely poor communication between individuals with unique learning structures - where do they find common ground to relate experiences and understanding? “Culture forms minds” [12] and it is through these shared experiences as a member of the same culture that individuals’ understanding is configured in a way that allows effective sharing with those around them. Still, the Constructivist framework does not seek to define a ‘shared meaning’ - it is non-trivial to say with certainty that two individuals associate precisely the same meaning with a statement or object - instead Constructivists seek “compatibility, a lack of contradiction between views” [24] also termed ‘viability’.

2.4 Ways of Learning: Formal Versus Informal

Marsick and Watkins [62, pp. 12] describe Formal Learning as “typically institutionally sponsored, classroom-based, and highly structured” [62] while Informal Learning is described as a “usually intentional but not highly structured” [62, pp. 26-30] activity that can be purposefully implemented by an institution or can take place free of asserting forces, driven purely by a learner’s own interest.

Historically academia has been slow to adapt to the varying needs to learners [17, pp. 1]. Biggs [8] discusses in some depth the “blame-the-student theory of teaching” whereby students that do not learn effectively are assumed not to be capable of learning well, or not wanting to learn enough. He concludes that this is not a way of teaching but of being selective in those individuals that educators choose to educate at each respective level (delineated by assessments) and that students who do not learn effectively under the current system simply need to be *engaged* more effectively.

Hofstein and Rosenfeld [48] discuss the importance of tailoring instruction to an individual learner’s “abilities and aptitude” [48]. A variety of instructional strategies and learning materials are important for increasing the efficacy of an individual’s learning [102]. Eraut [17, pp. 12] is careful to emphasise that formal learning plays an important part in education and that the two different categories of learning are complementary rather than mutually exclusive ways of learning.

2.4.1 Formal Learning

When contrasting the two different categories of learning Eraut [17, pp. 12] describes formal learning as consisting of:

- “A prescribed learning framework;
- An organised learning event or package;
- The presence of a designated teacher or trainer;
- The award of a qualification or credit;
- The external specification of outcomes” [17, pp. 12]

Davies [17, pp. 54] describes formal learning as “the framework of curriculum and qualifications, prescribe[d] content and assessment arrangements” [17, pp. 54]. Formal Educators try to “manage the environment in a way that is not possible for informal educators” [50, pp. 16] and “set out with a much tighter idea about what is to be achieved” [50, pp. 16].

In work that supports the theory put forth by Coffield [17, pp. 1] which states that elements of *all* learning are Informal in nature Benson Snyder [96] wrote a book entitled “The Hidden Curriculum”. He relates his experiences in an educational setting where he was “struck repeatedly with the importance of a hidden agenda, a hidden curriculum” [96, pp. xii] which alters the meaning of the traditional curriculum, in the case of a male student altering “not only what he will learn but how he will learn it... Covert, inferred tasks, and the means to their mastery are linked together in [the] hidden curriculum” [96, pp. 4]. The hidden curriculum is often invisible to educators and rarely discussed amongst students being “a semi-private matter, shared with roommates and certain classmates” [96, pp. 2] at most. Snyder describes the hidden curriculum’s formation as an “exercise in time budgeting” [96, pp. 62] or a “selective-negligence task” [96, pp. 49] in which the student engages to do the minimal amount of work required to achieve the desired grade.

2.4.2 Informal Learning

Informal learning is described by Frank Coffield [17] as “much more significant than any of us had previously realised” [17, pp. 1] and that there is a continuing trend for the academic community to forget the significance of informal learning only to rediscover it some years later [17, pp. 2]. Coffield [17] goes on to highlight how much of life is learned informally, from parents, the reactions of friends or from emulating those around us - describing it as a “way of surviving formal education” [17].

Eraut [17, pp. 12] describes three different kinds of informal or ‘non-formal’ learning:

- **Implicit Learning:** The passive acquisition of knowledge which occurs even with “no intention to learn and no awareness of learning at the time it takes place” [17, pp. 12]

- **Deliberative Learning:** Time specifically set aside for the acquisition of knowledge outside of a formal environment [17, pp. 12]
- **Reactive Learning:** Lying in between Implicit and Deliberative learning and “used to describe situations where the learning is explicit but takes place almost spontaneously in response to recent, current or imminent situations without any time being specifically set aside for it” [17, pp. 12]

Entwistle [28, pp. 22-25] discusses the evolution we undergo as learners from a child at primary school, to a university student. Younger children are often encouraged to learn using a wide variety of means that are *provided* for them inside a given framework whereas at a higher level students very much evolve into “self-learners”, hunting through books and journal articles for information they need to complete a relatively free form, or open to interpretation task.

Environment is an important factor for Informal Learning to take place. Coffield [17, pp. 54] states that the “setting in which learning takes place is associated with its informality” [17, pp. 54] and McGivney [69] describes Informal Learning as learning that takes places outside of a “dedicated learning environment” [69]. Such variation from ‘traditional’ methods has often caused caution to be exercised in the application of Informal Learning in many educational settings [17, pp. 56].

Mobile theory is considered to complement the practice of Informal Learning [93]. Aspects of Informal Learning are “fundamentally mobile” [93] and an attribute of mobile learning is a user group of “informally arranged and distributed participants” [93]

2.5 Evaluating Learning

For some time the favoured method of evaluating why people learn well involved looking for commonalities between subjects. For example, those who were good learners “were found to be intellectually more able, more highly motivated, and better organized” [65, pp. 12–13]. Marton et al. [65, pp. 12–13] discuss an “alternative paradigm” for “empathetic understanding of what is involved in student learning”.

This technique involves discussing student's thoughts and feelings about learning in order to diagnose potential faults in the manner in which knowledge is being imparted. The authors [65] also note that "traditional research approaches" are too lecturer-centric in their categorization of students. Entwistle's 1975 Study [25] for example contains labels such as "disorganized and dilatory" and "cynical and disenchanted" which "goes beyond labelling; it becomes libelling and an attribution of responsibility" [65, pp. 13]. Parlett and Hamilton [41] were among the first to publicise this 'illuminated evaluation' as a viable alternative to the then-current system of trait-analysis.

Marton et al. [65, pp. 24] discuss a trend of teachers trying to identify "*how much* is learnt" with the emphasis being on quantity, rather than "*what* is learnt" with the emphasis being on the quality of the knowledge retained by the student. This is the sort of analysis that Phenomenography can be applied to readily, students can be asked to comprehend a passage in an assessment exercise and relate it back in a way that signals their understanding of the complex issue described. Popular in this method of evaluation are "semi-structured or thematic interviews" [65, pp. 24] the interview being careful not to give any clues which would bias results.

2.6 Chapter Summary

A deep learning approach, or a hybrid deep-surface approach seen only in certain cultures [64, pp. 39] emerges as the best way to learn [66] [32] [28]. Motivation plays a vital part in learner attention and engagement [100] [107] [26] aided to some degree by our natural drive for knowledge [79]. Different methods of constructing and analyzing what has been learnt exist and can prove valuable in retention of knowledge [8] [27] [24] [82, pp. 49] and a combination of formal, informal and collaborative learning creates a powerful learning environment [8] [23] [28, pp. 22-25].

The next chapter examines technologies that are available to assist those learners vying to reach their full potential by learning Informally, outside of the classroom and on their own schedule.

Chapter 3

Learning Technologies

3.1 Introduction

In order to develop suitable methods of promoting informal learning it is important to explore the methods and techniques employed in previous research as well as emerging technology that can present new study opportunities. This chapter starts with an introduction to the needs of Informal Learners, followed by a description of Object Tagging and the advantages/disadvantages that its different implementations engender for learners. Next it introduces Recommendation Algorithms, enumerating the various types and exploring in detail those that are suitable for this thesis before summarising many of the key technologies contained herein to conclude the review.

3.2 The needs of Informal Learners

Informal learning is a casual, often mobile (Section: 2.4.2) activity. Learners must be aided by tools that are highly accessible and as mobile as they are.

3.2.1 Information Quality

When tagging objects, the quality of information that is offered should be accurate and up to date. Rieh [87] defines Information Quality at an “operational level” as “the extent to which users think that the information is useful, good, current, and accurate”. Within Rieh’s [87] exploration of Information Quality on the web he also

explores the notion of *Cognitive Authority* - the degree by which “users think that they can trust the information”. For a learner to trust a resource, it must have both a high perceived Information Quality, as well as an acceptable measure of authority from their point of view [87]. In the world of printed publications these measures are often inferred from “reviews, refereeing processes, and the reputation of publishing houses” [87] whilst in the online world they are judged based on past experience of a source, and the method by which it was discovered (referral or search engine). For a user to trust an online source which anyone can create and publish however, it should be both reputable and refereed to instigate authority as well as trust [87].

3.2.2 Mobile Interaction

The mobile user device is a relatively new tool in the learning domain, it is slowly being realised as a valuable tool in mobile learning which features heavily in a 1998 Green Paper, *The Learning Age*, released by the UK Government [76]: “In future, learners need not be tied to particular locations. They will be able to study at home, at work, or in a local library or shopping centre, as well as in colleges and universities ... Our aim should be to help people to learn wherever they choose and support them in assessing how they are doing and where they want to go next”.

A number of factors may be considered important when designing a tool for learning that can be deployed to multiple, mobile devices at once which are approached below.

3.2.3 Interconnectivity

Interconnected devices offer a range of options for mobile software developers, Bluetooth, described in Section 3.3.3 allows active interaction with other users [16] in a peer-to-peer style and, on a much larger scale interconnected mesh networks of wirelessly connected devices can work in parallel towards a common goal or can be so small as to inform a corporate user when a ‘tagged’ device is leaving a building (e.g. Smart Dust [74]).

Interconnected technology has been the source of many “Social Location-based

Services” such as “Lovegetty” the matchmaking system that beeps or flashes when it is close to another compatible device and “GeoNotes” the “location annotation software available on [some] mobile devices” [75]. The social element is an important one that can also be applied to a collaborative context - as a society we already send emails wirelessly and can chat by voice/instant message on the move. Bellotti and Bly [7] show that “mobility may be critical to many work settings that have been traditionally considered non-mobile” and that the technology required transcends simple video-conferencing or email and compounds the importance of Computer Supported Cooperative Work (CSCW) packages supporting it.

Many aspects of the internet are prime examples of Interconnected technology at its most-used; many users on many devices are collaborating to produce a desirable output. Mainstream Wikis, Social Networking and Social Bookmarking sites are all heavily used and there is already evidence of this interactive, collaborative technology manifesting itself in mobile applications from the work of researchers such as Smith et al. [95] and Maness [61]. As described in Section 2.2.2 collaborative learning has been shown to provide enormous benefit in many different situations, and a large part of the success of many of these systems is the ability to quickly propagate knowledge gleaned to a wider readership - enriching their learning experience in the process.

Social Bookmarking or ‘Tagging’ especially separates itself from the rest for mobile use as it requires much less typing or description and is often based around visual or audio sources, the former being the basis for applications such as ‘GeoNotes’ [33]. Mobile devices, notably more recent mobile telephones lend themselves to audio-visual recording and as a result could make ideal devices for use in ‘Mobile Tagging’. User-based, rather than centrally-controlled, tagging is a ‘collaboratively structured’ approach to classification with users assigning their own labels and has gained a variety of labels such as “folkonomy”, “folk classification”, “ethn classification”, “distributed classification” or “social classification” [42].

3.2.4 Intelligence

Intelligent interaction between devices is an important part of a successful application. Ciavarella and Fabio [16] find, when considering a HIPS-style [77] infrared grid for user detection (described in Section 3.3.3) that it is very difficult to determine whether a stopped user is stopping to admire a piece of museum artwork, or simply stopping to queue or talk with another user. Intelligence could have been added to their application to attempt to determine this, based on stopping time and a history of past interactions but was deemed too complex in comparison to the final solution.

3.3 Object Tagging

3.3.1 Introduction

Presenting information to learners is a key element of attention and engagement [3]. ‘Tagging’ physical objects with information that is of interest to a learner or ‘consumer’ has been an area of research led largely by commercial applications, notably museums [16] and city tourist guides [14].

Tagging objects for information in a manner where information can be centrally or collaboratively updated (such as on the internet) rather than more traditional static methods such as plaques or posters presents obvious advantages in getting the most up to date and applicable information to a recipient. For the purpose of this review tags can be categorized into *visual* such as a designated ‘information point’ and *non-visual* offering a more seamless user experience, such as a museum user walking through infrared ‘gateways’ to initiate an information download or other learning trigger [16]. “Typically, interaction with a [visual] tag employs a physical gesture where the user (or more precisely, user’s device) points at or touches a tag” [60] whereas non-visual processes require less action on the part of the user to have information presented to them.

A large amount of space is usually implicit when discussing tagging items in a physical area - items to be tagged are very rarely clustered in a confined environment such as the space surrounding a desktop terminal. To that end, users often interact

with tags using a mobile device such as a ‘smartphone’ or PDA. Such devices are increasingly internet-ready although in a recent experiment Makela et al. [60] discovered that users expected tags to contain direct, textual information about the item to which they were attached and “were surprised when [a] recognized identifier triggered a browser which then retrieved information from the internet”. In the same 2007 study it was determined that of 50 participants only 39% had owned a camera phone (despite all participants having a phone of some description) which may indicate an age-related lack of awareness or adoption. In a study of mobile phone ownership in 2001 Katz and Aakhus [54] discovered that teenagers and young people (20-29) are more likely to own a mobile phone and “have quickly learned how to use mobiles as fully as possible” [54, pp. 20-21]. Mobile phones are ideal devices for mobile tagging activities, being “ubiquitously available devices, constantly within reach of the user” [90].

Rohs and Gfeller [90] discuss possible application areas for mobile tagging technology - “the ability to detect objects in [a] user’s vicinity strengthens the role of mobile phones in e-commerce, education, and gaming scenarios” offering a “natural way of interaction [making] data entry more convenient” mobile phones effectively serving as a “kind of ‘bridge’ between entities in the real world and associated counterparts in the virtual world” [90]. Since many types of tag “can only encode a limited amount of information, they normally serve as a key that is resolved to the actual data of interest” such as a URL or ID number.

Rohs and Bohn [89] experiment with tagging in a campus environment using “physical hyperlinks” that they term “entry points” - “visible entrypoints into the information space” or “information anchors” - which correspond in spirit to Fitzmaurice’s [36] idea of “situated information spaces” - meaning being virtually attached to physical objects in a contextually-appropriate manner. These broad categories eventually came to be what is currently known as *augmented reality* - the quest to enrich the purely physical world with virtual additions like information, 3D supplements and other augmentations that are appropriate to a user’s context. Each “physical hyperlink” in the Rohs and Bohn model has “virtual counterpart[s]” [89] which “represent physical objects in the virtual world” and this terminology is an

accurate way of addressing the relationship between physical tag and the data it directly (as part of the tag) or indirectly (as part of a URL/linked content) contains. In the Rohs and Bohn [89] system “virtual counterparts also process events and capture relationships with other virtual counterparts. Relationships between virtual counterparts are dynamic and evolve over time as a result of user actions and other events” - leading to a more personalised and relevant experience for each user.

Gellersen [38] describes the concept of “Environment-Mediated Communication (EMC)” whereby an “instance [or object] in the physical environment serves as a link between [some] communication partners” and cites examples of many of the things we see tagging used for today: “*Physical message transmission*” - attaching a message to a physical object (e.g. an office door) for retrieval at a later date by the same or a different person, “*Location-bound-delivery*” - information that should only be retrieved in a certain location, “*Location-bound-send*” - which encodes a user’s location, such as Geo-coded Tweets¹, “*Virtual EMC*” - virtual visitors to a real-world physical location (Virtual/Augmented Reality). Figure 3.1 shows the relationship Gellersen describes between the information source (‘SRC’), the intermediary physical location and the place the information is ultimately retrieved from (the ‘SINK’) - having a “physical instance as mediator” enables both source and sink to be unaware of each other, enabling the entire physical information tagging model which “reduces information overload” [89].



Figure 3.1: In a simple example of EMC the chain of communication would resemble this. [38]

3.3.2 Visual Tagging

Visual tags can be physical markings to indicate an area of interaction with an otherwise invisible tagging technology or printed tags such as those seen in aug-

¹The Twitter Blog: <http://blog.twitter.com/2009/08/location-location-location.html>

mented reality applications like *Cybercode* [85] and tag-based educational exploration games [13].

In some augmented reality applications users can hand-draw glyphs from a pre-established library which are then recognised by software [68] effectively crowd-sourcing the task of glyph placement to anyone with an appropriate degree of knowledge about the system - a type of collaborative tagging. Outside of an established role or task, or where there are a large number of objects that users would be required to remember this system knowledge can be difficult to retain. Additionally, there is an onus on the designers of such a system to create a symbol ontology that is sufficiently representative of the external world which can be non-trivial [98, pp. 85] [43].

Visual tags can take many forms and the rest of this section is dedicated to enumerating prevalent members of each type and their technical capabilities:

Two Dimensional Barcodes

Two Dimensional barcodes offer significant advantages over the typical one dimensional barcode, namely:

- “Information is encoded digitally, as opposed to the analog encoding of data in conventional barcodes” [99]
- Scalability: A code being written and read typically only depends on the granularity of the technology involved in the process [99]
- Error Correction: Increasingly modern, digital barcodes support error correction (such as Reed-Solomon codes [108]) [99]

Early two dimensional barcodes were simply stacked traditional (1D) barcodes, over time they evolved into the more modern ‘matrix code’ that we see in popular use today². Matrix codes are often created for different purposes, from tracking parcels and mail to identifying parts on an assembly line and are considered an “interesting

²QRCode Specification and license information: <http://www.denso-wave.com/qrcode/aboutqr-e.html>

option” in the domain of object identification “because of the basic technology and simplicity of the concept” [91]. These barcodes can be printed using any standard print hardware and as a result are cost-effective and straight-forward to produce relative to other technologies such as RFID [91].

Terminology Typically two dimensional barcode symbologies encode their information in a “checkerboard pattern of on/off cells” [99] referred to simply as ‘the pattern’. All the examined two dimensional barcodes feature their own variation of a “finder pattern” which allows decoding devices to locate the code and assess its type quickly and efficiently.

Many two dimensional barcode technologies are proprietary and these are mentioned purely for comparative reasons since their use in any research project would be infeasible.



Figure 3.2: A QRCode example

QR Codes The QRCode was developed by Denso-wave in 1994. The open specification is publically available and the patent right owned by Denso-wave is not exercised to allow innovation. QR Codes are an approved ISO standard (ISO/IEC18004)³ and are capable (at their largest) of storing up to 7,089 numeric characters, 4,296 alphanumeric characters or 2,953 bytes ². This type of code can encode virtually any kind of data “including symbols, binary data, control codes, and multimedia data” as well as supporting the Japanese Kanji and Kana character sets [53].

³ISO/IEC18004: http://www.iso.org/iso/iso_catalogue/catalogue_ics/catalogue_detail_ics.htm?csnumber=43655

In Japan QR Codes have become popular and can be seen in “advertising, in the print media, on business cards, products, websites and vending machines” [106]. Recent developments of the trend have seen it used by companies such as Google⁴ and Pepsi to market their products to a worldwide audience.

Like other codes in its class, the QR Code can be reconstructed in its entirety if up to a maximum percentage of the code is damaged. When a code is created encoding can be set for correction levels L, M, Q and H which correspond to maximum loss areas of 7%, 15%, 25% and 30% respectively. Pattern duplication is kept to a minimum by employing one of eight masking techniques selected by the encoding software at runtime. As standard QR Codes are encoded with a “structured-append” ability which allows any one code to be broken up “into up to 16 data areas” which are reformed upon decoding [53].

Advantages for learning research include a high adoption rate and hence an abundance of resources to work with. Also, an emerging familiarity with QR Codes as companies utilise them to boost product sales makes these codes a tool that can be easily used and employed.



Figure 3.3: A Data Matrix example

Data Matrix The Datamatrix was invented by RSVI Acuity Cimatrix and is also publically available and can be used free of any royalties. It is an approved ISO Standard (ISO/IEC16022) ⁵. Data Matrix codes of a maximum 144 x 144 grid size can store up to 3,116 numeric characters, 2,335 alphanumeric characters or 1,555

⁴The Android Market: <http://www.android.com/market/>

⁵http://www.iso.org/iso/iso_catalogue/catalogue_tc/catalogue_detail.htm?csnumber=44230

bytes.

Data matrix codes are often used in industries such as PC Circuit Board manufacture where they are recommended by professional associations [99]. Their ability to be small in size, easy to process and be printed in low-contrast directly on to parts make them ideal for this application. Data Matrix codes can be manipulated to smaller grid sizes, which affects how much data they can retain. Examples of capacity at smaller sizes are shown in table 3.1.

Symbol Size Row X Column	Data Capacity		Code Size
	Numeric	Alphanumeric	7.5 Mil. Cell
10 x 10	6	3	1.9 mm
12 x 12	10	6	2.3 mm
14 x 14	16	10	2.7 mm
16 x 16	24	16	3.0 mm
18 x 18	36	25	3.4 mm
20 x 20	44	31	3.8 mm
22 x 22	60	43	4.2 mm

Table 3.1: “Storage capacity for Data Matrix codes of various sizes” [99]

Error checking and correcting (ECC) levels of 000 to 200 are available for Data Matrix codes, with the most common being ECC-200 which employs Reed-Solomon error correction to reconstruct missing sections of the code. Preceding levels of error correction offer up to “five different error-correction levels and use convolutional code-error correction” [53]. For the purposes of this review only ECC-200 will be discussed.

The “L-shaped solid border [of a Data Matrix code] defines the physical size, orientation, and symbol distortion, and the broken border on the opposite corner defines the symbol’s cell structure.” [53] - comparatively to QR Codes Kato [53] performed an experiment in which “eight digits were encoded in a .25 mm cell”, the Data Matrix consistently “created the smallest symbol (3.3 x 3.3 mm) and maintained the same level (10-15 percent) of error correction”. Like QR Codes a

Data Matrix symbol can also be separated into up to “16 multiple symbols” which can be scanned in any order to reconstruct the original data.

Semacodes A semacode is a trade name for machine-readable ISO/IEC 16022 Data Matrix Symbols, which encode internet Uniform Resource Locators (URLs) and other textual data⁶.

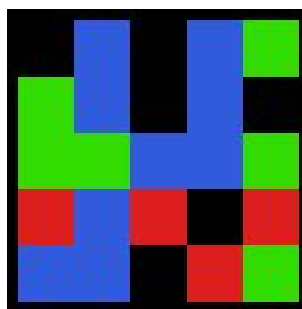


Figure 3.4: A ColorCode example

ColorCode (Proprietary) Often referred to as a “3D Barcode” for adding the extra dimension of *colour*⁷. Colorcode is marketed as an Index-code, requiring a connection and subscription to ColorzipTM’s service to function. A “standard ColorCode tag encodes 10 digits and comprises a matrix of 5 x 5 cells rendered in a combination of four different colors - black, blue, green, and red. Cells can be circles, ovals or polygons.” [53]. Because different printing devices can produce Colors (and hence ColorCodes) differently and to protect decoders against variations in lighting or paper quality the barcode standard employs a “reference cell” that serves as an example to allow any decoder to determine the particular colour and hue of the standard set of colours in each case. As a further measure of error correction the “ColorCode includes an *error parity check* that detects any incorrect colour recognition and corrects it. The exclusive operation of code values in each column and row becomes the code value of the parity cell for the respective column and row, which the encoder converts to its corresponding colour value in the symbol’s parity area.”

⁶Semacode Corp.: <http://semacode.com/about/company.html>

⁷ColorzipTM: <http://www.colorcode.com.sg/index.php>

Notably “ColorCode decoding only requires 40 percent visibility of an individual cell. So you can easily incorporate a barcode into ... some graphic design, making the most of the remaining 60 percent of the symbol’s space” [53].



Figure 3.5: A Shotcode example

Shotcode (Proprietary) Developed by High Energy Magic Ltd. and originally known as ‘Spotcode’ the Shotcode is a “derivative of another circular 2D-barcode tag or ‘ringcode’ known as a TRIP (Target Recognition using Image Processing) tag or TRIP code.”. “TRIP tags encode a ternary number from 1 to 19,683 using two concentric rings surrounding a bull’s-eye target ... two rings are divided into 16 sectors. The first sector (the synchronization sector) indicates where the TRIP code begins. The subsequent two sectors store an even parity check on the encoded identifier (TRIP code), which detects possible decoding errors. The following four sectors encode the radius of its central bull’s-eye in millimeters. The remaining nine sectors encode a ternary identifier.” [53]

Since Shotcodes cannot hold alpha-numeric characters they are made available as an ‘Index Tag’ rather than a ‘Data Tag’ meaning that they are something which “links the real world to the digital world by accessing remote databases” [53].

Reed-Solomon Error Correction

Error correction codes are “used to add redundancy to data to make it fault tolerant (up to a certain degree)” [57]. Reed-Solomon Error Correction codes are widely deployed across many technologies where large amounts of data are involved such as DSL internet connections, DVD/Blu-ray discs and of course the data matrix/barcode tagging technologies mentioned in this chapter. The codes are designed

September 29, 2010

by “oversampling a polynomial constructed from the data [to be transferred]” resulting in redundant data points. The transmission message is then mapped to a polynomial and the codeword is “defined by evaluating it [(the oversampled polynomial)] at several points”.

Koetter [57] provides a generalized formal definition of a Reed-Solomon code:

Generalized Reed-Solomon (GRS) Code

Let $\underline{\alpha} = (\alpha_1, \dots, \alpha_n)$ be the locations where the Generalized Reed-Solomon code is evaluated, with $\alpha_i \neq \alpha_j$ for all $i \neq j$. Let $\underline{\lambda} = (\lambda_1, \dots, \lambda_n)$ be the non-zero normalizing coefficients. Then, the $GRS(n, k, \underline{\alpha}, \underline{\lambda})$ code is defined as the set of codewords:

$$\{(\lambda_1 f(\alpha_1), \lambda_2 f(\alpha_2), \dots, \lambda_n f(\alpha_n)) \mid f(x) \in F_q[x] \text{ with } \deg(f(x)) < k\}$$

The redundancy created in the initial oversampling allows the original data to be reconstructed even in the presence of some ‘bad points’ up to the measure of redundancy in the ‘block’ of data that makes up a transmission. Assuming no prior knowledge of the location of errors in data (i.e. no *erasures*) the Reed-Solomon code can correct up to $(n - k)/2$ erroneous symbols where $n - k$ is the measure of redundancy in the block.

Reed-Solomon codes are especially suited to ‘bursts’ of errors in data rather than sparsely distributed ‘bad points’, this explains their common use in media and barcoding technologies where data is most likely to be corrupted or distorted in this manner.

Comparisons of Two Dimensional Barcodes

Kato and Tan [53] analyzed recognition rates of QRcodes, Data Matrix Codes, Shotcodes and Color Codes using ‘First Read Rate’ (FRR) as the measure - “dividing the number of successful first reads by the number of attempts made (50) to read each sample”. For each type of barcode there were four samples - each pair of samples (two pairs in total) contained the same data in differing sizes (2.5cm^2 and

5.0cm²). Error correction was set at the most common, or code-specific levels; 15 percent for QR Codes, 28-39 percent for the first Data Matrix sample and 22-34 percent for the second data sample.

A VGA Mobile Phone Camera and a 1.3-megapixel camera were used for a camera-quality comparison (between FRR and Camera Resolution) and captured codes from between 5 and 25cm away using “Cold Cathode Fluorescent lights under three lighting conditions” [53] - half power, full power and ambient lighting only (normal fluorescent room lighting). The test was performed by a previously non-skilled user who was given the chance to trial several kinds of barcode scanning before engaging in the experiment.

Their results in Figure 3.6 show a clear readability benefit for index-based 2D Codes such as Shotcodes and Color Codes with the former being recognised 100 percent of the time, regardless of “lighting condition, symbol size, camera resolution or data quantity” and the latter falling to 97.9 percent by the same measure. There was significant variation between performance of different software used to read the codes in the experiment (for example the *Kaywa* QR Code Reader versus the *Quick Mark* equivalent). In the case of QR Codes, the lesser software failed at a greater distance away from a small printed code while the lesser software used for decoding a Data Matrix varied in ability across all scenarios with the same point of worst recognition (scanning a small code from far away).

Data (URL)	Symbol size (sq.cm2)	Data Matrix		VSCode	QR Code		Visual Code	ShotCode	ColorCode
		Kaywa reader VGA/1.3M	Semacode reader VGA/1.3M	PC reader VGA/1.3M	Kaywa reader VGA/1.3M	Quick Mark reader VGA/1.3M	Built-in reader VGA/1.3M	Built-in reader VGA/1.3M	Built-in reader VGA/1.3M
Short	2.5	100/100	97.3/97.3	88.7/77.3	100/100	100/100	100/100	100/100	98.0/98.0
	5.0	100/100	99.3/99.3	100/87.3	100/100	100/100	100/100	100/100	98.0/96.7
Long	2.5	100/100	69.3/14.0	60.0/54.6	0/0	100/100	100/100	100/100	98.0/98.6
	5.0	100/100	93.3/92.0	95.3/100	100/100	100/100	100/100	100/100	98.0/97.3

Figure 3.6: Mean First Read Rate (FRR) percentage for each 2D barcode in different data quantities, symbol sizes, and camera resolution. [53]

In the comparison of camera quality needed for good FRRs [53] found that resolution made no difference, with the lower quality VGA camera actually performing better than the 1.3-megapixel camera (in terms of FRRs) in most cases. Kato and

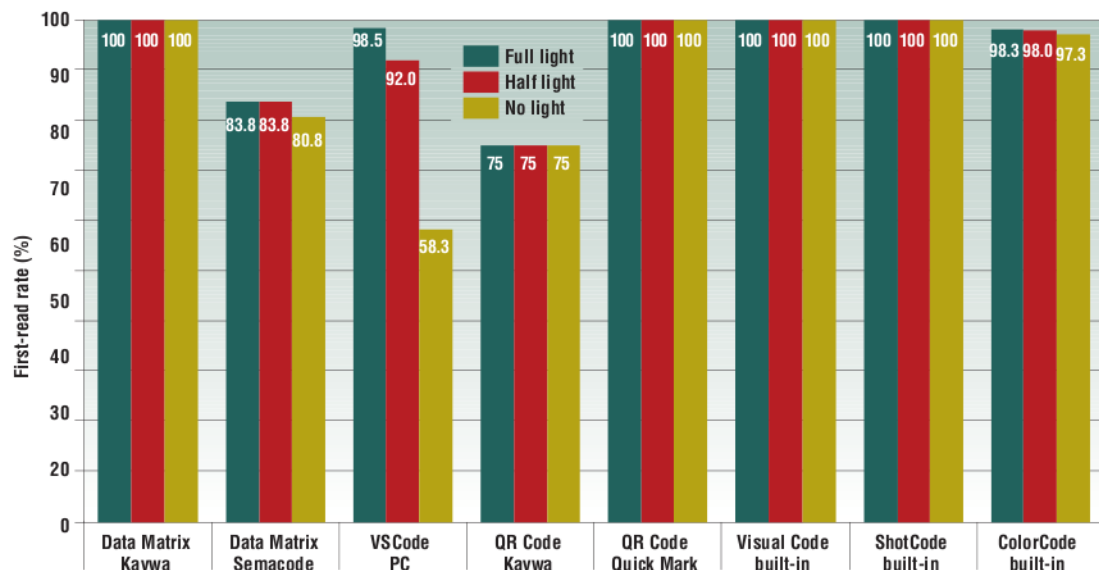


Figure 3.7: A summary of results obtained by Kato and Tan [53]

Some of the codes mentioned are not being reviewed.

Tan [53] do acknowledge that other camera features such as autofocus and light sensitivity may have affected reading accuracy so this result cannot conclude definitively that lower camera resolution is always better - other factors such as “reader software, and programming languages” can also affect the outcome.

In terms of “maximum legible distance” database barcodes (QR Code, Data Matrix) outperformed index-based barcodes by 4.8cm (21.7cm compared to 16.9cm) with some readers and code types (e.g. Kaywa/Data Matrix) being able to average 56cm reading distance for the larger symbols. Kato and Tan [53] go on to demonstrate an at least linear relationship in code size: “Generally, the reading distance doubled when the symbol size doubled, regardless of the code type. However the reading distance of the double-sized dense database symbols nearly tripled” the latter fact possibly being due to the level of error correction employed.

Kato and Tan summarise their work into three factors which are key to improving the “robustness of 2D-barcode reading” which are:

- The cell size of symbols
- The software’s decoding algorithm
- The decoding device’s hardware capability

Summations

This research creates a strong case for the Data Matrix and QR Codes with very little difference in their recognition over distance, and symbol size. Due to the similarity in their implementations the two types of code have many of the same advantages and disadvantages and the decision on which is best to use for visual tagging becomes a matter of software support, and ease of use.

3.3.3 Non-Visual Tagging

Non-visual tagging often revolves around various granularities of *location*. This may involve passing through an infrared gateway [16] or having your location detected by GPS [14] or another method such as wireless triangulation. ‘Information Beacons’ can be triggered via technologies such as bluetooth with no interaction from the user. Such systems of non-visual tagging are often termed “Nomadic” [77].

Work by Ciavarella and Fabio [16] in this particular type of tagging is extensive. Their focus is Museums and how a small handheld device (PDA) can be utilised as a location-aware tour guide application. Initially their goal was for interaction to be *passive*: “users will not have to navigate a potentially complex menu, or interact with buttons or barcodes to access information about the exhibit that they are viewing. Additionally the service needed to ”‘be provided without disorienting the user”’ [16].

After various evaluations Ciavarella and Fabio discover many users feel a “lack of control” when using their system and hence introduce *active* interaction measures to deal with their concerns over the degree of control users of their application may experience. Active interaction measures include a button to allow the user to choose when to move on to new information, rather than having the device update itself when a new location beacon is detected. This allows the learner to work at his/her own pace and indicates that a fully passive solution hindered, rather than aided the learners’ workflows.

RFID

RFID tags present an invisible, near field of communication. They can be active or passive. The former has its own power source, such as a battery and can transmit signals autonomously whereas the latter requires another source to power it (e.g. by induction) to provoke transmission. Active tags have been demonstrated with ranges of up to 100 metres [94] although typically this is as little as 10 centimetres without special antennae [60]. A similar situation applies to some passive tags which can have a range of up to 21 metres when using the correct equipment [55] but have a very low range otherwise.

Despite being an ostensibly non-visual tagging technology it is still necessary to know vaguely where an RFID tag is to be able to interact with it. This could be near an object or location or the location could be clearly marked on a surface such as a door or wall. Without these indications it would only be possible to find tags by trial and error or by implementing an active-tag/passive-detector system that would see all tags broadcasting simultaneously creating potential issues with high levels of ‘noise’ in enclosed environments.

Bluetooth

“Bluetooth is a de facto standard for very low powered connections” [16] and allows users to connect easily from distances of up to 10m [21]. Unfortunately this is offset by a per-connection initial ‘discovery’ time of “between 5 and 10 seconds” [16] as well as limitations on the amount of learners that can be on any given beacon at a time which can inconvenience other learners by causing wait times, or confusion between ‘tags’.

Bluetooth is heavily used in the mobile device sector, most often for connecting to components such as headsets and in-car audio kits. Once an initial connection is ‘paired’ future pairings are relatively fast. In a similar fashion to RFID bluetooth beacons would need to be marked to improve user awareness despite the underlying technology being non-visual. This is mitigated in bluetooth to a degree by the larger range (when compared to RFID) of the system and the ability for a tag device to dynamically contact other devices around it informing them of its presence. This

problem does add to the ‘noise’ described in Section 3.3.3 however, which with no indication of distance from a uni-directional source will flood a user with beacons ‘requesting attention’.

Infrared

Infrared (IR) is most commonly recognised as the Line of Sight (LoS) technology used in remote controls. Ciavarella and Fabio [16] explore “Infrared beacons” as an interaction technology. Infrared supports data rates of up to 4mbps [21] and is “characterised by non-interference with other electronic devices” [16]. The technology is relatively cheap due to its abundance in modern culture. Because of the LoS nature of IR the sender and receiver must be within a thirty degree cone angle of each other for communication to be effective. [16]

Eventually Ciavarella and Fabio [16] realise that without a complex IR grid it would be difficult, if not impossible, to glean a user’s exact location within their museum at any given time. Due to the expense of such a grid (an example of which can be seen in the HIPS project [77]) they opted to use a ‘portal’ approach, triggering messages for users as they pass certain IR points or beacon broadcast areas. While this system is now functional in a purely passive manner, there are some aspects which [16] believe a user would like to control, the ability to stop audio clips playing for example, or the ability to browse back to an exhibit they viewed earlier which lead to the addition of the ‘active interaction’ features described earlier in this section.

Location-Based

Location based methods have a significantly larger range than other technologies approached in this section although granularity can be much more coarse depending on the technology selected. There are various popular methods of obtaining the physical location of a device. It is of note that these methods simply access data that is already being broadcast in many areas passively, without sending their own signal to indicate presence or command response.

GPS The Global Positioning system is part of a satellite-based navigation system developed by the U.S. Department of Defense under its NAVSTAR satellite program. It provides signals “for geolocation and for safe and efficient movement, measurement, and tracking of people, vehicles and other objects anywhere from the earth’s surface to geosynchronous orbit in space” [70]. GPS Positioning is based on the triangulation signals from at least three of the 24 satellites in orbit. To “produce accurate positions in three dimensions” [70] at least four satellites are necessary to create an appropriate “precise signal intersection”.

Due to the distance of satellites from earth one significant caveat of the GPS system is that signals are rarely able to penetrate structures and hence, can only be relied upon when a receiver is outside in a relatively open space.

When the appropriate number of satellites are in range however GPS can allow triangulation of positions with an accuracy of up to 10 metres on standard equipment moving up to between 1 and 3 metres of accuracy when using “expensive differential units” [46] providing unrivalled accuracy of location virtually anywhere in the world. Increasingly GPS receivers are being added to mobile consumer devices creating an enormous worldwide network of location-aware devices.

Due to its poor indoor reception GPS has not been used exclusively for information discovery projects such as Ciavarella’s [16] Museum Tour Guide. Instead designers of learning tools often opt for a hybrid approach that employs GPS when it is available but falls back to other methods when it is not.

Wireless Triangulation Wireless triangulation implementations are extremely expensive with at least three and preferably four access points being required for effective locating [46] of any given device in an area. The benefits of such a system are a relatively well supported, high speed (approximately 4-5Mbps of throughput [21]) solution while other weaknesses include high power utilisation on a small mobile device and potentially issues with many overlapping access points in a confined space [16].

This method assumes that the precise positions of access points are known otherwise objects in an ad-hoc network can only calculate their own position relative

to one another only. The accuracy of Wireless Triangulation is significantly better than GPS on standard hardware at 1-3 metres on average [46]. The time and computationally expensive operation of measuring “radio time[s] of flight” can put strain on “power and computationally constrained devices”.

Wireless Vector Location Wireless Vector Location is a less computationally expensive alternative to Wireless Triangulation. Batty and Kyaw [6] discuss the method of representing a physical location by using a “representative vector” consisting of a range of available signal strengths from nearby wireless transceivers. Since “wi-fi signal strengths vary noticeably over time. One smoothing technique is to sample a fixed number of times, then take the mean” to create a relatively reliable average measure.

This method is typically applied when measuring the similarity between two locations. Taking the dot product of two vectors $(1 - v_1, v_2)$ consisting of 2-tuple elements containing a wireless access point and a normalised signal strength then produces a relative indication of distance or *difference* between the respective points.

3.4 Recommendation Algorithms

3.4.1 Introduction

When searching a corpus of items, the approach adopted by many is to utilise the title and content of the item, as well as any additional metadata to perform a textual search, known as content-based filtering [44]. Results are then usually ranked by their similarity to the original query and presented to the user in the resulting order [11]. Moderate recommendation results can often be achieved by this method although it requires content to be easy to analyze (e.g. text) and ignores user definitions of quality and taste [44]. For improved accuracy Breese et al. [11] describe collaborative-filtering based recommendation algorithms as a “complementary method” for content-based filtering that do not suffer from similar pitfalls. Typically such systems are based on “usage or preference patterns of other users” and are typically built on the assumption that “a good way to find interesting

content is to find other people who have similar interests,” [11] and then recommend titles that those similar users like.

In many ways Collaborative-filtering (CF) recommendation systems can be portrayed as superior to content-based alternatives, Herlocker et al. [44] highlight the ability to attain “serendipitous recommendations” from a system that relies on user opinions and ratings rather than content which prevents a user from having to enumerate exactly what they are looking for in a recommendation in order to have it presented to them at all. The authors conclude however that for a recommendation technology to “reach the full potential, it must be combined with existing content-based information filtering technology” [44].

CF-based recommendation algorithms represent an area of significant research. It has proven non-trivial to predict users’ needs by using an algorithm that attempts to cater for all users without examining their *context* - elements such as previous buying behaviour, ratings, reviews and interactions. The “most successful technolog[ies] for building recommender systems to date” [22] are user-based collaborative-filtering algorithms that involve the user of a system’s choices and views in the algorithm itself. Deshpande and Karypis [22] define a *Recommender System* as “a personalized information filtering technology used to identify a set of items that will be of interest to a certain user” which accurately summates the purpose of the intended recommendation system for this study, identifying a set of items that will be of interest to a certain *learner*.

Common problems in the recommendation field are the:

- **Prediction Problem:** Predicting whether a user will like a particular item
- **Top-N Recommendation Problem:** “Identifying a set of N items that will be of interest to a certain user“ [22]

3.4.2 Collaborative-Filtering Based, Top-N Recommendation Algorithms

Collaborative filtering systems have come to prominence in the last 20 years [44] with the first researchers to use the term being Goldberg et al. [39] when they created

September 29, 2010

an email filtering program called Tapestry. Tapestry allowed users to annotate messages using certain guidelines empowering other users to specify queries that would use this metadata to filter out unwanted messages. This system did not produce recommendations, users had to construct often complex queries themselves but it established the basic principles of Collaborative Filtering that would govern further research. Today collaborative filtering systems are described by the “notion of multiple users ‘sharing’ recommendations, in the form of ratings, for various items” [1] - this effectively creates a cost/benefit situation whereby the *cost* of rating objects is offset by the benefits of “collective group knowledge”.

“Collaborative filtering systems are often distinguished by whether they operate over implicit versus explicit votes” [11]. Explicit votes require the user to consciously rate an item, usually along a discrete numerical scale (e.g. one (very bad) to five (very good)) whereas Implicit voting is a background activity that observes user behaviour such as past purchases, location history or other patterns to form a ‘weight’ for an item [11] [44].

In their encompassing literature review Deshpande and Karypis [22] describe two approaches for developing CF-based top- N recommender systems:

The **user-based** approach as the name suggests concentrates on the relationship between users, or groups of users. For example in an e-commerce system the items that one user buys may be what a user with a similar context to them also purchases. Conversely, the **model-based** approach focuses on the relationship between items, or groups of items for example that certain items are commonly purchased together, or that when one group of items are bought another group is also likely to be purchased next based on historical records.

Model-based schemes usually “produce recommendations very quickly” [22] after constructing models from historical data. This measure can require a “significant amount of time” in relation to a user-based algorithm depending on the number of users and items. For larger scales, where a high number of users are involved there are significant lookup-time advantages to be gleaned from model-based algorithms. Typically however model-based algorithms produce recommendations that are “generally of lower-quality than those produced by user-based schemes” [22].

User-based algorithms, without the benefit of entirely pre-calculated models (which become non-trivial to generate in a large user-based scheme) become more complex on a linear scale in relation to the number of users and/or items in their database presenting “serious scalability problems” [22] for larger systems.

Because of corporate interest in algorithms such as those described a vast amount of research concerning them is oriented towards buyers, sellers and large user corpora. For the purposes of this thesis it is generally safe to replace the idea of a *customer* with that of a *learner* whom is choosing objects to examine rather than to purchase.

Model-Based Algorithms

Deshpande and Karypis [22] describe two key areas of a Model-based CF Recommender Algorithm that affect performance. The “method used to compute the similarity between the items” and “the method used to combine these similarities” so that a group of items can be compared to one “candidate recommender item”. These methods are the central topic of research between the two types of CF Recommender algorithm with many corporate researchers (such as Amazon’s [59]) concentrating on the highly scalable model-based options using techniques such as vector cosine and conditional probability measures [22] to reach a measure of similarity between items.

Measuring Item Similarity Clustering is a recurring theme in the literature for model-based methods of measuring similarity amongst items [11]. Calculating item-to-item measures can be time-expensive and calculating measures instead across clusters of similar items can afford significant computation-benefits in larger systems. The underlying principle is that “there are certain groups or types of users capturing a common set of preferences and tastes” [11] from which such clusters can be constructed.

Previously documented methods for measuring similarity between users include:

- *Pearson’s Correlation Coefficient* - a well known method for measuring the linear dependence between two variables. This method was used in several

early publications [86] [44] [47].

- *Bayesian Classification:* Using user-provided ratings that are used to construct “decision trees at each node” [11] which ultimately can be combined in such a way that contains “set[s] of parent nodes that are the best predictors for [a] child’s rating” [22].
- *Graph Methods:* Aggarawal et al. [1] describe a graph-based method of collaborative filtering based on the concepts of *horting* and *predictability, p*. In the graph nodes represent users and edges represent *p*. This measure of predictability encompasses a wider range of users than Pearson’s Correlation Coefficient measures, including pairs of users where one person is more “effusive” with their ratings than the other. The “ultimate idea is that [a] predicted rating of item *j* for user *i* can be computed as weighted averages calculated via a few reasonably short *directed paths* joining multiple users”, none of whom have rated *j* [1]. This model allows the “capture [of] transitive relations which cannot be captured by nearest neighbour algorithms” [22].

User-based Algorithms

Generally user-based algorithms “compute the top-N recommended items for a particular user by following a three-step approach” [22]. To summarise:

1. Identify users in the application’s database that are “the most similar to the active user”
2. Combine the sets of items “purchased” by the users and “associate a weight with each item based on its importance in the set”
3. Select the items with the highest resulting weights that have not already been purchased by the user

Deshpande and Karypis [22] go on to observe that the most critical elements of this “three-step framework” are the method used to identify users in Step 1 and the weighting or importance method for items described in Step 2.

The scalability issues of User-based algorithms in comparison to those based on item-item schemes can be mitigated by clustering users and pre-calculating similarity measures between these constructs. Searches on a per-user basis can then be limited to the nearest clusters rather than the entire database which avoids the problem of severe latency in large systems seeking to provide recommendations in real-time. [44] [103] [72]

Measuring User Similarity Breese et al. [11] imply that it is unrealistic to expect a complete set of ratings across all items to base recommendations upon. “In most applications, users will vote on items they have accessed, and are more likely to access (and vote) on items they like” [11]. To combat this problem some collaborative filtering algorithms make “assumptions about the nature of missing data” which can improve their performance [11].

In User or “memory-based” [11] algorithms employing a ‘weight’ or ‘rating’ system for nodes, the goal is to predict the votes of the active user based on partial information about them and “a set of weights calculated from the user database” [11]. When reviewing various methods of comparing users to find similarities between them Breese et al. [11] utilised a definition of the “predicted vote of the active user” to be a weighted sum of the votes of other users in the system. Definitions may vary but in the same manner as Breese et al. [11] this thesis adopts the convention when discussing comparative measures.

Calculating the **similarity between users** is often measured via “cosine or correlation coefficient functions” [22] (across user-item purchase vectors) whereas items are often **weighted** by how frequently the most similar users to the target user purchased them. [22] [11] [92].

Previously documented methods for measuring similarity between users include employing:

- *Pearson’s Correlation Coefficient* - See section 3.4.2.
- *Vector Comparison Methods* consisting of 2-tuple items containing a title and rating can be employed to create a measure of similarity between the rating activities of two users to determine whether their interests coincide [11].

Restrictions with this method include the fact that all ratings constitute a positive vote for an item (as unobserved items garner a zero rating) which is mitigated in some studies by only including those votes that are deemed positive (e.g. higher than neutral on a typical five point scale).

Work by Breese et al. [11] applies a measure used in information retrieval termed “inverse document frequency” to Vector Comparison Methods the governing principle of which is that “universally liked items are not as useful in capturing similarity as less common items” [11]. The revised frequency of an item under this method can be defined as:

$$f_j = \log \frac{n}{n_j}$$

“where n_j is the number of users who have voted for item j and n is the total number of users in the database... if everyone has voted on an item j , then the f_j is zero.” [11]

3.4.3 Chapter Summary

Informal learning is an exceptionally free ranging and casual activity and technology needs to accomodate this. Mobile devices such as those used by [16] [33] [74] [77] are important in guaranteeing necessary mobility and extracting as much context as possible using technologies such as GPS, Wireless Location and user databases can serve to vastly improve the effect of recommendation algorithms attempting to assist the learning process.

In the next chapter a tool to approach the research questions posed in section 1.4 is presented using the research contained in the previous chapters to govern its own methods.

Chapter 4

QRCode Tourist: A tool for exploring tagged objects effectively using context-sensitive recommendations

4.1 Introduction

Helping learners approach subjects in a meaningful way plays a prominent part in education. Lesson plans, classroom quizzes and presentations all work towards building a foundation of knowledge that can then be augmented in future teaching. Informal learning lacks this rigid structure; With no guidance learners are free to delve into information which they may not understand. If this information is properly connected it could help them establish new building blocks for future knowledge acquisition, engage them with other learners who share their interests and provide an efficient and engaging method of learning outside the classroom.

This tool seeks to approach this problem of connection and engagement, encompassing Informal Learning's often ad-hoc and disjointed nature to empower and motivate potential informal learners to expand their knowledge away from a formal setting. The requirements can be related to the research questions that this thesis poses and accommodate technologies and strategies described in previous chapters to

form a set of implementation goals, which are enumerated below:

4.1.1 Supporting the principles of Informal Learning

Aim: Augment Informal Learning trying not to interfere with the process. Relates to Research Question(s): R1, R2

Informal learning is a casual, often highly mobile activity (See Section 2.4.2) and the choice of platform for the tool should be able to support this. Learners should be able to choose what to learn about, and be able to change their mind in line with their interest.

4.1.2 Provide a method of tagging and reading tags for arbitrary objects in a physical space

Aim: Provide a method of tagging, and reading of tags for arbitrary objects in a physical space. Relates to Research Question(s): R1

The tool should offer a tagging solution that is obvious to learners and targets this thesis' goal of promoting Informal Learning on a wider scale as well as providing information just for those who are using the tool itself. High learner-awareness of the tagging method chosen and good usability will reduce barriers to participation and allow for casual use in-line with existing definitions of Informal Learning (As described in Section 2.4.2).

4.1.3 High Quality Information should be created for items

Aim: Create high-quality information that is connected to additional resources that learners will be able to access. Relates to Research Question(s): R1, R2, R3, R5

Section 3.2.1 described the factors that define high quality information. In addition item information should be up to date, encompassing hyperlinks and electronic media such as audio clips to encourage learners to engage at a level that they find comfortable. The information attached to each item will form the backbone of the tool's learning experience and should use multiple sources to produce detailed and accurate entries.

4.1.4 Learners should be able to rate items

Aim: Provide a system of rating objects for collaborative-filtering Relates to Research

Question(s): R1, R3, R4, R5

Rating of items provides a basis for collaborative-filtering for use in recommendations as well as assessing whether learners were interested in the objects that they were viewing.

4.1.5 Log Usage Statistics

Aim: To log quantitative data to be used in the evaluation of the tool and the generation of recommendations. Relates to Research Question(s): R1, R2, R3, R4, R5

In order to produce quantitative results the tool must calculate and report the following metrics:

1. *Number of items scanned per user*
2. *Frequency of scans on a per-item basis*
3. *Distance travelled between items*
4. *Number of times an audio clip is played*
5. *Depth of exploration within data (level of clickthrough)*
6. *Which recommendations, in which position, were selected*

4.1.6 Create a recommendation algorithm that aims to provide high-quality recommendations to learners

Aim: Use a learner's context and the actions of users that can be deemed 'similar' to create tailored recommendations Relates to Research Question(s): R1, R4, R5

A collaboratively-filtered, top-N recommendation algorithm should be created that will present learners with a list of related items that they may be interested in viewing based on their personal context and the activities of other learners who are similar to them.

4.2 Platform

When selecting a platform for the tool, familiarity with the type of device used will mitigate some of the learning barriers to operating a new tool for the first time, such as basic knowledge of common keys or options and the intrinsic knowledge of how such a device functions in a learner's everyday life. A common platform such as a desktop operating system, mobile phone or portable music device would offer such advantages.

Chapter 3 described several technologies that can be used to glean contextual data about a user including wireless connectivity, GPS and access to online databases. Additionally the ability to accept user commands by keypress or touch is essential allowing learners to use the tool at a pace and in a manner that best suits their personal preference.

Programmability is an important function of any platform, this thesis cannot hope to develop advanced tools such as those described within this chapter without a mature, stable, feature-filled and well documented software offering.

Bearing all of these criteria in mind, a mobile phone platform was selected as the ideal platform for the tool. Mobile (Smartphone) devices offer the best combination of portability and connectivity/contextual features as well as being devices that an enormous majority of learners are aware of and use regularly. In 2009 there were more mobile phones in the UK than people: 75.565m (2008) phones versus 61.113m (2009 est.) people [104] while in 2003, 88% of 15-34 year olds in the UK were confirmed to own a mobile device¹.

The most prominent mobile operating systems were ranked subjectively based on their respective feature sets, these results are summarised in Figure 4.1.

The tool is to be developed using Windows Mobile, and C#.NET. A large community provides excellent software support and Windows Mobile devices are popular, with the manufacturers of such devices holding significant worldwide market share.

¹UK Office of National Statistics, "Adult mobile phone ownership or use, by age 2001 and 2003", <http://www.statistics.gov.uk/STATBASE/ssdataset.asp?vlnk=7202> (Accessed: September 2009)

Mobile Platform	Approximate Age (years)	API Maturity	Community/Support	Developer Tools	Approximate Users
Android	1	1 (Evolving)	5 (Very Good)	2 (New)	2.8%
Windows Mobile	6	4 (Quite Old)	4 (Good)	5 (Excellent)	9%
Symbian	8	5 (Very Old)	3 (Moderate)	4 (Good)	50.3%
Blackberry/RIM	10	5 (Very Old)	3 (Moderate)	3 (Moderate)	20.9%

Table 4.1: A subjective comparison of various mobile platforms as of December 2008. All scores are out of five unless indicated otherwise

4.2.1 Hardware Device

The HTC Touch 3G (Figure 4.1) provides a well-balanced (in terms of computational ability) device offering support for wireless and location-based technologies as well as a large touch-screen for learner interaction and information display.



Figure 4.1: The HTC Touch 3G

4.3 A method of tagging and learning about objects

4.3.1 Tagging Objects

The QRCode or Data Matrix presented themselves in Section 3.3.2 as the most versatile two-dimensional barcodes. A visual tagging system, based on a data-code rather than an index code is appealing for a multitude of reasons:

- Highly visible, promoting awareness, curiosity and accessibility and by extension making the tags a ‘target’ for Informal Learners.

- Allows for wider variation in data stored. Data-based tags could hold links to external or internal websites and short descriptions.
- Can be utilised by learners who are not taking part in this study, providing a learning method that is independent of the type of software used to read tags.

In the drive to offer a tool that is “obvious to learners” (Section 4.1.2) the QRCode was selected as the most appropriate medium for tagging objects. Recent media campaigns and a high level of popularity with consumers in some countries means that awareness of the code is significantly higher than its counterpart, which is most commonly seen in manufacturing.

Each QRCode was an encoded link to an item-specific location on the study’s web page. Using hyperlinks instead of static data allowed better usage tracking, the ability to manage information centrally and the use of web technology provided ready access to hyperlinking of additional resources including digital media.

4.3.2 Learning About Objects

Software provided by Google’s Zebra Crossing² project allowed for the online decoding of QRcodes involved in this project. Wirelessly connected learner devices contacted a ‘cloud’ service geared to quickly decode and return the contents of QR-Codes.

Upon receipt of the Uniform Resource Locator (URL) stored in each item’s QR-Code, the tool launched a customised, full-screen web browser to display information about the object to the learner.

4.4 Creating information for objects

Object information will be created by aggregating an assortment of online resources that would typically be available to an Informal Learner. Using multiple public sources of data and other ‘related links’ increases reliability and decreases the time-intensive nature of creating bespoke entries for large numbers of items. Regardless

²Google Zebra Crossing Project: <http://code.google.com/p/zxing/> (Accessed: February 2010)

of this fact, aggregating and confirming referenced information is a time-intensive process for educators engaging in a tagging process can not trivially be mitigated.

The physical location of each item was measured as a normalised to one wireless vector averaged over one hundred readings for accuracy (Section 3.3.3) to allow the difference in position of the learner between separate scans to be estimated.

4.5 User Ratings

Displayed directly below the information for any given item was a ratings panel that allowed learners to rate items from 1 (Very Bad) to 5 (Very Good). Each item could only be rated once and recommendations could be changed retrospectively if desired.

Ratings were instantly stored in a central database over the device's wireless link as they occurred enabling other parts of the tool to utilise the most up-to-date ratings data at any given point.

4.6 Logging Usage Statistics

The tool was configured to log usage statistics to a MySQL database in the following situations:

- When a scan succeeded and/or an item's entry was shown
- When a scan failed
- When viewing an items entry, the number of times a user clicked a hyperlink
- After selecting a hyperlink from an item's entry the number of subsequent hyperlinks that were then selected (clickthrough depth)
- When a recommendation was selected

4.7 Development Process

A fast, iterative development process was employed during the development of the tool rapidly creating prototypes of the various components before integrating them into a final product. This offered significant advantages for a one-person development team performing comprehensive testing at integration-time after a series of incremental, and corrective builds. Later in the experiment we employed a pilot study which, at least partially, assisted with final software testing (described in Section 5.2).

4.8 System Architecture

The tool consists of four distinct components obeying a (Web) Service-Oriented model of communication. Despite the application being completely portable the ever improving level of global wireless coverage, especially within this study's experimental setting in the heart of a university campus, provides ample resource and ability to utilise this model in a way that would have been extremely difficult in earlier years. The client-server, service-oriented model of communication allows for central storage of data and 'cloud based' calculations that would be too complex for a relatively low powered mobile device to perform in a respectable (from the user's perspective) amount of time. This saves phone resources, and in some cases is faster than building a completely client-side application with all appropriate data on the device.

4.8.1 Component Diagram

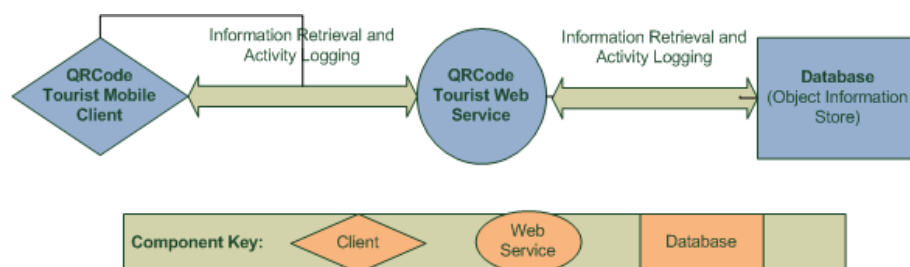


Figure 4.2: A diagram of the components that make up the QRCode Tourist Tool

4.9 Recommendations

A collaboratively filtered, user-based recommendation algorithm was created to to serve learners with a ‘top- N ’ ranked list of other objects that they may be interested in. The algorithm took into account various elements of user context and behaviour to create this list which are described in table 4.2.

Variable	Formal Representation
User Invariants	
Academic Department	d
University College	c
Year of Academic Study	y
Course of Study	s
Academic Status (Undergraduate/Postgraduate/Staff)	a

Table 4.2: A list of the variables involved in the computation performed by the QRCode Tourist Tool’s Recommendation Algorithm.

Learners could filter the results of the recommendation algorithm from within the QRCode Tourist application. The filter allowed learners to see all items, or only ‘new’ items - that they had not seen before. Throughout this section the *active user* refers to the learner who is using the QRCode Tourist application to retrieve recommendations at the time of computation.

Definitions Let D^v, C^v, Y^v, S^v, A^v be the set of the top 20, most viewed items for a particular group of users identified by User Invariants, d, c, y, s, a . For example, D^v represents the set of the top 20, most viewed items identified by users in the same *Academic Department* as the active user.

Let D^r, C^r, Y^r, S^r, A^r be the set of the top 20, best rated items for a particular group of users identified by User Invariants, d, c, y, s, a . For example, D^r represents the set of the top 20, best rated items identified by users in the same *Academic Department* as the active user.

Let G and H be the set of the top, most viewed and most rated items respectively across all users and G_n be the ranking of a particular item, n within them.

Let J be the set of objects that are most similar to the active user's last known location, or null if this is the first object scanned. Location similarity is calculated by taking the *dot product* of two normalised wireless vectors v_1, v_2 such that v_1 represents the position of the last item the active user viewed and v_n represents the position of an item n .

Similarity Algorithm Each item in the set is assigned a weighting, w , based on its order in each set (i.e. 1st place has a higher weighting than 20th). Additionally an initial, subjective importance measure of specific User Invariants was assigned to provide an appropriate bias. In each case location (i.e. physical convenience) was awarded the most subjective bias and weaker measures consisted of groups with wider memberships such as the same university course or same university college.

The overall similarity rating of a particular item, R_n , and hence its similarity to other items that the active user, or people like the active user have viewed can be calculated as:

$$\begin{aligned}
 R_n = & (0.1 - N(C_n^v)) + (0.1 - N(Y_n^v)) + (0.25 - N(S_n^v)) + (0.2 - N(D_n^v)) + (0.1 - N(A_n^v)) \\
 & + (0.15 - N(C_n^r)) + (0.3 - N(D_n^r)) + (0.15 - N(Y_n^r)) + (0.2 - N(S_n^r)) + (0.1 - N(A_n^r)) \\
 & + (0.2 - N(G_n)) + (0.4 - N(H_n)) + (0.5 - N(J_n))
 \end{aligned} \tag{4.1}$$

Each weighting component (w) consisting of $y - N(X_n)$ where X_n is the ranking of item n in one of the top 20 user-invariant-based sets D, C, Y, S, A and y represents the maximum possible weighting (i.e. the weighting received by the top-most ranked item). $N(X_n)$ can be calculated as:

$$N(X_n) = \frac{\sqrt{N}}{50} \tag{4.2}$$

Items were presented to the user in a *top-N* list, ranked by w .

4.10 Screenshots

Screenshots demonstrating each facet of the system are available in Appendix A.1, each of the three images shown is described in detail below.

- **Image 1:** This image illustrates the recommendation screen, where unseen ('new') or all seen ('all') items could be exposed to the participant for their consideration. Additionally this screen displayed a tailored rating for each item, as the value determined by the recommendation algorithm (Section 4.9).
- **Image 2:** From the 'main screen' illustrated in *Image 1* the participant could elect to scan a barcode, an activity portrayed in this image.
- **Image 3:** Finally, when viewing information for an item the learner could capitalise on richly linked information featuring audio and textual aspects to explore the scanned learning object in depth. The option to rate an item added to further enhance their experience, serving as an input to the recommendation algorithm described.

4.11 Chapter Summary

In this chapter the QRCode Tourist Tool has been presented. This system is deployed to learners on mobile devices and gives them the ability to scan pre-positioned tags that link to information aggregated from well-known public sources that learners themselves are able to access.

As more items are viewed the tool tailors recommendations for the active user, and users who are similar to the active user based on a selection of invariants (Table 4.2) and data on the learner's last known location versus the position of potential items for the learner's consideration.

The next chapter describes the evaluation of the QRCode Tourist Tool in the form of a learning task based on campus at Durham University.

Chapter 5

Evaluating the QR Code Tourist Tool

5.1 Introduction

The QRCode Tourist tool presented in this work can be evaluated from different perspectives with various methods. The tool seeks to make informal learning more “effective” this means that the information it provides must be considered relevant by learners, that recommendations created by its recommendation algorithm are pertinent and that it is easy for a learner to use it and learn whenever they desire. There are various methods of evaluating a user interface and other aspects of software individually [49] but the primary focus of this work is on informal learning and improving that process. To effectively draw conclusions as to whether learners find the tool useful and effective a real-world case study or experiment lends itself as the best solution.

Typically research focuses on either the actions of subjects during an experiment or a series of targetted exercises (such as interviews and questionnaires) at different points in the process. This evaluation elects to use a hybrid solution consisting of observations and analysis of actions during the experiment coupled with focused inquiries at different intervals that will allow it to fully identify the strengths and weaknesses of the work presented in this thesis.

Due to the logistical challenge of creating an experiment consisting of physically

tagged objects across an entire campus, a case study was constructed using the ground floor of a central building on the Durham University Campus as the Learn-scape. Various methods were employed within this study to assess the tool, and its intended learning outcomes:

- **Participant questionnaires** Questionnaires were constructed for completion before and after the experiment. The focus is to determine how helpful the tool was for the task as well as gauging the subject's level of expertise with software/technology as an above-normal affinity could influence outcome. Additionally free form sections at the end of each questionnaire invited participants to share their thoughts and feedback on any part of the process.
- **The Think Aloud Protocol** Learners were encouraged to *think aloud* [105] through out the process covering topics such as what they were doing, why they were doing it and anything else that occurred to them such as elation or confusion.
- **Analysis of learner actions** Tool-based recording of actions, paths and errors can be used to determine the success of the learning task as well as being employed to varying extents by the context-sensitive recommendation algorithm.

This chapter describes the selected method of evaluating the QRCode Tourist tool enumerating in detail the chosen evaluation metrics and conditions of the experiment. A description of the demographic of participants viable to be selected for this experiment concludes the chapter leading in to the analysis and presentation of results in Chapter 6.

5.2 The Learning Task

The evaluation took part over a twelve week period, this consisted of a Pilot Study - to help highlight any obvious pitfalls and the Study itself. Participants were all students or academic members of staff at Durham University.

Participants were each presented with a Mobile Device (HTC Touch 3G)¹ with the latest version of the QRCode Tourist Tool installed and running. Instructions on how to use the barcode scanner and very basic details of the purpose of the experiment (i.e. that it has to do with *Informal Learning*) were included in a pre-experiment set of instructions (Appendix A.2). Based on difficulties experienced with software use during the Pilot Study a pictorial set of instructions for using the Barcode Scanning aspect of the tool was also presented (Appendix A.1).

Participants were asked to progress through the *Calman Centre* scanning any barcode tags that interested them for a minimum time of fifteen minutes. They were encouraged to only scan the tags that interested them and could end their participation before the end fifteen minute period if they truly lacked any motivation to continue. If participants did elect to finish the experiment before the allotted time the researcher would attempt an informal interview to determine their reasoning focusing on whether it was due to difficulties or matters unrelated to the experiment. Additionally participants were directed to use all aspects of the tool where possible including the ratings and recommendation systems.

Items that were ‘tagged’ in the Calman Centre varied, by far the most prolific was an on-going art exhibition entitled ‘Scopic’ which compared and contrasted astronomical and biological photographs and artistic interpretations created by students in London and County Durham schools². These Scopic pieces made up 25 out of 32 objects tagged for this study. Other objects included portraits of the building’s namesake, Kenneth Calman, vending machines and the cafe in the public space as well as the reception area and computer kiosks. A full inventory of the Learning Material for this task (tagged items and the data associated with them) can be found in Appendix A.3. Sources of information for items include the official documentation for the Scopic exhibition, The Encyclopedia Britannica, Wikipedia and other assorted, publicly available online references.

¹HTC Touch 3G: <http://www.htc.com/www/product/touch3g/overview.html>

²The Scopic Exhibition: <http://www.royalalberthall.com/explore/projects/project.aspx?id=1778>

5.3 Assessment of Learning Outcomes

Qualitative assessment of the learning outcomes for the QR Code Tourist Tool was performed using questionnaires as many of the outcomes focus on the learner's *motivation*, benefits of the tool *as they perceive them* and *impressions*. More quantitative data was also gathered from questionnaires as this section of the thesis describes as well as via technical measures such as click-through rates and scanning logs.

5.3.1 Pre-Questionnaire

A pre-task questionnaire allowed the gathering of demographic data about each participant which can be cross-referenced with other data during the analysis of results to help explain unpredicted patterns or anomalies (for example, younger participants may be more at ease with the use of technology and hence more interested in what the tool offers for their learning) as well as information about the subject's past experiences with technology and whether they had interacted with a visual tagging system before (approaching research question R2). This questionnaire is attached as Appendix A.5.

When considering research question R2, those participants that use computers regularly are expected to be more at ease with the use of a tool such the QRCode Tourist as well as those with prior experience of mobile internet browsing, use of location based services, application development or web design.

5.3.2 Post-Questionnaire

A post-task questionnaire was formulated (Appendix A.6) to contribute towards measurement of the learning outcomes of this thesis.

A summary of the questions contained, and their relevance to the learning outcomes can be found below. Sections P1-P5 are likert-scale questions neutrally phrased:

[P1] General

This section attempts to highlight any usability issues with the software, which could explain potential lack of motivation or dissatisfaction with performance in the learning task. The questions approach the ability to navigate the software as well as the barcode recognition system which plays a significant role.

[P2] Objects

Focusing on tagged items, this section of the questionnaire approaches research question R1 asking participants whether they thought information was informative and/or interesting. These questions will help assess the quality of the information that has been entered into the system.

[P3] Recommendations

Targetting the recommendation subsystem this section asks what the learner thought of the recommendations that they were provided with, combined with data from technical measures this will allow the research question R4 to be approached.

[P4] Surroundings

The Surroundings section is an attempt to determine if the participant felt that people in the very public area selected for the experiment were detrimental to their performance, such environmental factors are important for determining the source of any unexpected results (external factors/influences).

[P5] Audio

Centered on the audio clips contained in the object information provided by the tool, this section makes sure the learner was aware of the clips and asks them to rate their usability. Finally the content of the audio clips is rated for quality, all contributed to question R3.

[P6] Distance

Direct, single-selection multiple choice questions about whether the participant would travel a distance to view items displayed for them by the recommendation subsystem acts to strengthen conclusions for R4 and can be generalised for contributions to question R5.

[P7] Freeform Feedback

A free-form feedback section concludes the questionnaire and allows participants to identify anything that the questionnaire may have missed or that they would like to add. Such feedback can be very valuable in identifying unforeseen difficulties or identifying parts of the tool which perform very well.

5.3.3 Focus Groups

All participants were asked whether they would like to take part in a post-task focus group, at a date to be determined. Focus groups can be used to help explain anomalous results, giving a researcher further insight into the issues that are of “particular relevance to a topic and set of respondents” [97].

A focus group will consist of semi-structured interview questions in a casual setting to support interactivity. If possible, multiple focus groups will be used to provide “a broad range of viewpoints and insights” [58].

5.3.4 Contextual Data

The following elements of user context were available to use for each participant from the Durham University Database, each item of context is followed by a description of why it is considered relevant:

- **University College:** Place of residence, or affiliation if not residing on university property. Those living in a college physically near to the site of the experiment may also be inclined to travel to view recommended objects.

- **University Department:** Technical qualifications may heavily influence results, Computer Scientists and other technical disciplines are considered to have a higher aptitude for this task despite efforts to the contrary.
- **Enrollment Status:** Either Undergraduate, Postgraduate or Academic Staff. Enrollment status yields a measure of research experience, which in itself can influence how subjects interact with an experiment and generate more
- **Course of Study:** Students from the same course may find the same items interesting or respond more positively to the tool as a group.

Additionally the device uses wi-fi vectors to imply a **physical location** as described in Chapter 4. Each tagged object's position was measured using the same location method so that distances between objects and distances between the user and the objects could be calculated.

5.3.5 Ratings

It is predicted that more user ratings will make the recommendation algorithm in the tool more likely to present the user, and users like them, with an object that they would like to see. The number of ratings made by users is logged and this is correlated with recommendation satisfaction over time.

5.3.6 Technical Measures

The tool was configured to log the following metrics:

- **Clickthrough Rate and Depth:** Clicking a link in a piece of the information provided lead to a depth of '1' being recorded, if the learner then progressed from that page into another the depth becomes '2' and so on. In this way it is hoped to see which learners are engaging with the information provided, additional exploration would imply that they are filling gaps in knowledge that will allow them to create a complete knowledge model for the scanned object, or a related topic (Research Question R1).

- **Number of Tags Scanned:** Scanning a relatively high proportion of tags out of the 32 available could indicate a highly motivated individual or a ‘surface learning’ approach to the task. Similarly a low number of scanned tags could indicate a very ‘deep learning’ participant or a laxidaisical approach to the task. This measure will be combined with other metrics in an attempt to decide which approach was selected by participants. Additionally, close analysis of the data may reveal trends across contextual data boundaries. All of these factors will contribute to Research Question R1. The number of tags scanned may also reflect positively or negatively on the recommendation subsystem (Research Question R4) and will again need to be combined with other data to make a conclusion.
- **Number of Scan Failures:** Occasionally a tag may not be recognised, this can be due to poor lighting or a poor photograph of the tag itself. If some tags regularly fail to scan this may aggravate users unnecessarily, biasing other results. Additionally this could indicate a deficiency in instructive material or an underlying problem with the tool itself.
- **Average Distance between tags scanned:** Distance between scanned tags can give an indication of the path a learner was taking through the Learnscape, multiple large distances could indicate a very casual pattern that saw them pass the same objects multiple times whereas smaller distances could indicate a systematic approach to the task as they navigated the space.
- **Audio clip usage:** Approached Research Question R3, usage of audio clips would indicate interest but to determine usefulness it is necessary to take the learner’s feedback from questionnaires into account.

Care was taken to make logging non-intrusive on the task experience so that participants were not interrupted while learning. Testing of the product was performed to ensure logged data was accurate and this was also verified manually with the small group of participants taking part in the Pilot Study.

5.4 Participant Demographic

The widest possible range of participants, to represent the wide range of potential learners was thought to be suitable for this task. Although encompassing very technical aspects of research, the final version of the tool must be accessible to those with varying levels of technical understanding. Advertisements for participants were placed on noticeboards across the university as well as wider access websites for students (such as Facebook.com and ‘Durham University Online’ - the Department of Computer Science’s internal mailing list was also leveraged to encourage participation from Computer Scientists, and their friends from other disciplines.

5.5 Limitations

It is possible to identify a number of limitations within the chosen method of evaluation, some of these result from the lack of an ideal scenario in which participants would spend hours experimenting with and assessing the tool while others are pitfalls that are prevalent among the various methods of evaluation employed:

- **Participants are provided with an approximate timeframe for their informal learning to take place:** Unfortunately it was not possible to structure the experiment in completely unattended and ‘informal’ manner. This is based on the small target area and the nature of the study (being primarily assessed by pre-study and post-study questionnaires) as well as a practical estimation of the amount of their own time that participants were available to give for research in an average day.
- **The study is limited to a defined area, and number of objects:** A defined target area results from the use of researcher observation and the think-aloud protocol (5.1) both of which brought significant benefits to the evaluation. Additionally participant availability (as mentioned above) played a role in the planned size of the study space.

Chapter 6

Results and Discussion

6.1 Introduction

A total number of 30 people consisting of students and academic staff from Durham University participated in the study. Five of these subjects took part in the pilot study (n=5) while the central study involved the remaining twenty five participants (n=25). This chapter describes the results gained from the study described in Chapter 5 and discusses their relevance to the desired Learning Outcomes from this task. It begins with a summary of results and analysis of trends within each set of data before combining respective datasets for further inspection. The chapter concludes with a summary of points highlighted in the discussion that could have improved the structure of this study.

6.2 Participant Summary

6.2.1 By Gender and Discipline

Of the 25 participants in this study 84% (n=21) were male and 16% (n=4) were female

6.2.2 By Degree Discipline

When cross-referenced with Degree Discipline (Figure 6.1) the proportion of male participants is unsurprising - Computer Science and Engineering are both fields populated by a vast majority of male students although female membership in the study's minority subjects (Anthropology, Biological & Biomedical Sciences, Geography and Government & International Affairs) is more significant¹. This result may be to do with the choice of venue, in a building on the University's Science Site with close proximity to the Computer Science and Engineering areas. Additionally an experiment using a new software tool on a mobile device, although only generally described in advertisements for participants may be more appealing to members of disciplines that feature regular software interaction.

6.2.3 By Age

The vast majority of participants were undergraduate students falling within the 18-25 age range. 24% though allow this experiment to make some judgements about the value of this tool with respect to the desired learning outcomes for the 26-32 age group as well.

6.2.4 By Computing Ability

All participants described their typical computer usage as 'daily'. The more specific questions about mobile, location-based and application development experience yielded the results shown in table 6.1.

Do you engage in this activity?	Yes	No
Mobile Internet Browsing	48%	52%
Use of mobile location-based services	48%	52%
Application Development (Software Engineering)	60%	40%
Web Development or Design	52%	48%

Table 6.1: Participant answers regarding computing activities.

¹Durham University Statistics: <http://www.dur.ac.uk/spa/statistics/undergraduate/2.4gender/2.4ft/>

The narrow majority of participants had engaged in Application Development and/or Web Design in the past (Figure 6.1), which correlates with the Computer Science Discipline majority. Typically those who said ‘no’ to application development also selected ‘no’ for all other parts of Q3 on the pre-task questionnaire while some participants who had developed software and web applications had not browsed the internet on a mobile device, or used mobile location-based services. This data represents a slightly above average but wide spread of technical ability amongst those taking part in the task.

6.2.5 Prior Experience of a Visual Tagging System

Although there has been various high profile campaigns such as Pepsi Co. Advertising and high-profile QRCode usage in Japan only 16% of participants had encountered a visual tagging system, or what they perceived to be a visual tagging system, before the task (Figure 6.2). This fact may create a level of ‘novelty’ which should be accounted for when making conclusions.

6.2.6 Other Invariants

A relatively even spread of mobile internet usage patterns reinforces the diversity of the technical experience of participants which helps results be more representative of those learners who are not themselves in very technical software-encompassing disciplines.

6.3 Summary of Questionnaire Results

6.3.1 General

Question	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Not Answered
The software was easy to navigate	0%	0%	4%	68%	28%	-
The barcode scanner was easy to use	0%	4%	8%	44%	44%	-
Barcodes were recognized quickly	4%	12%	12%	40%	32%	-
Overall, I found the system easy to use	0%	0%	4%	48%	48%	-

Table 6.2: Distribution of responses to the ‘General’ section of the post-task questionnaire

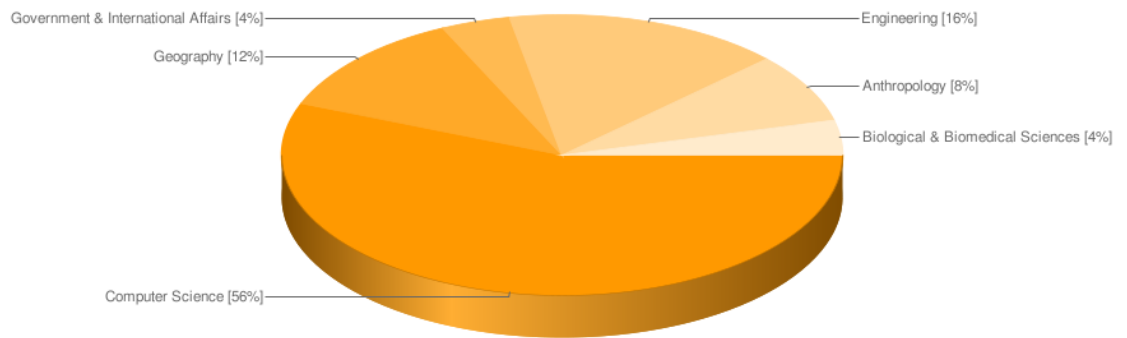


Figure 6.1: Participant Discipline Distribution

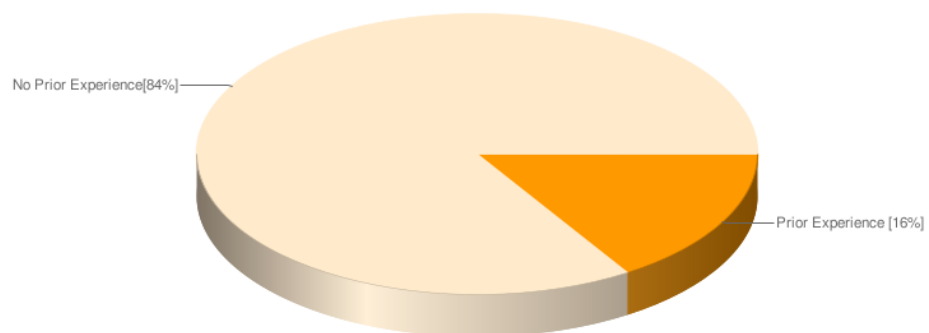


Figure 6.2: Prior Experience of using a Visual Tagging System Amongst Participants

From the results shown in Table 6.2 it can be inferred that the software was, for the most part, not difficult to use after the brief instruction provided. The barcode scanner was more difficult to interface with than the rest of the application (i.e. the recommendations subsystem), some participants obviously had issues with barcodes being recognized (quickly) which may be related to higher than anticipated scanning failure rates (Table 6.8). These issues however were marginalised in the overall view of the system's usability, indicating that the issues were not enough to completely invalidate the tool's user experience.

6.3.2 Objects

Question	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Not Answered
I found the objects that were tagged to be interesting	0%	16%	8%	60%	16%	-
Information provided about objects was informative	0%	0%	0%	56%	44%	-

Table 6.3: Distribution of responses to the 'Objects' section of the post-task questionnaire

The majority (76%) of participants agreed or strongly agreed that (tagged) objects around them were interesting while the remainder disagreed or were neutral on the issue (Table 6.3). No participants strongly disagreed with the objects interest which may indicate that other objects could have been interesting. This is reflected in some of the feedback in the freeform section of the post-task questionnaire, approached in section 6.3.6.

Quality of information was a potential weak point in the design of the tool as it was the same for each user, contextually tailored information has been found to be more effective for individual learning. All participants were positive about the quality of information provided however and no additional comments were received about length or composition.

6.3.3 Recommendations

Question	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Not Answered
The recommendations provided by the system seemed to coincide with my interests	0%	8%	32%	60%	0%	-
Recommendations were generated quickly	0%	0%	4%	52%	44%	-

Table 6.4: Distribution of responses to the ‘Recommendations’ section of the post-task questionnaire

There was a majority of ‘agree’ answers suggesting that recommendations largely coincided with the interests of participants in the task. A relatively high number of participants (32%) could not comment on whether objects selected coincided with their interests and some participants (8%) disagreed with the statement (Table 6.4). A more detailed examination of this data and the recommendation algorithm follows in Section 6.6.

Questions 13 and 14 focused on the recommendations provided by the tool and whether or not the recommendations that it provides would encourage them to travel some or no distance to see the objects presented and if that movement would be immediate or would occur at a later date. Durham University is made up of several small ‘sites’ each one containing multiple buildings. All sites are a distance from each other, travelling time between sites varies from approximately ten minutes to forty minutes on foot.

As highlighted in Table 6.5 all participants would travel some distance to view a recommended item, with the majority (56%) saying that they would move to a different building in order to view a recommended item. A minority of participants (20%) would travel to view recommended items immediately with the remainder electing to take a more opportunistic approach.

Question	Options	Number of Selections
What is the furthest you would travel to view a recommended item?	No Distance	0%
	Another Location in the same building	36%
	Another location in a different building	56%
	Another location on a different Durham University site	12%
When an item is recommended would you be most likely to...	Not travel to the object at all	0%
	Travel to it immediately	20%
	Remember the object for the next time you are in its vicinity	80%

Table 6.5: Distribution of responses to the ‘Travelling for Recommendations’ section of the post-task questionnaire

Question	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Not Answered
The Calman Centre was busy during the experiment	24%	24%	32%	16%	4%	-

Table 6.6: Distribution of responses to the ‘Surroundings’ section of the post-task questionnaire

6.3.4 Surroundings

The vast majority of participants did not feel that the assigned space was ‘busy’ with 32% not taking note of congestion at all (Table 6.6). This serves to ensure that participants did not feel rushed, or under pressure to complete a task or get distracted by others who may have impeded access to objects or other areas. Where possible tasks were scheduled outside of known busy times (e.g. around lectures) so that coordinating and performing the task was easy for participants. Additional complications when the task area was busy could have included poor access to objects and low visibility.

6.3.5 Audio

This was the only section of the questionnaire that some participants neglected to answer. Those that did answer (Table 6.7) indicated a majority awareness of audio clips although 32% of participants were not fully aware of this feature (those who

Question	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	Not Answered
I was aware of audio clips in the information provided	4%	8%	8%	40%	28%	12%
It was easy to play audio clips present in the information provided	8%	4%	28%	24%	16%	20%
Audio clips made the information more interesting	8%	8%	28%	16%	20%	20%

Table 6.7: Distribution of responses to the ‘Audio’ section of the post-task questionnaire

disagreed, did not answer, or remained neutral). This high number could indicate that the audio clips need to be better displayed within the information provided, with icons and/or a more obvious typeface to help users discriminate between them and normal hyperlinks.

Of those taking part in the task that completed Questions 11 and 12 40% believed that audio clips were ‘easy’ or ‘very easy’ to play and ‘agreed’ or ‘strongly agreed’ that audio clips made the information more interesting. A high level of neutral results indicate a lack of conviction that could reflect poor content in clips or could be a knock-on effect of poor visibility of these clips within object information. Alternatively, some learners could be indicating that audio clips do not add or detract from the learning experience but are merely an expected part (28% of participants indicated that audio clips did not make information *more* interesting).

6.3.6 Free-form Feedback

It was extremely useful to receive feedback from participants, and strongly encouraged throughout. Such feedback especially in the Pilot stages of this study provides invaluable insight into the tool and problems that may not have been obvious to researchers. 96% of participants agreed to participate in a Focus Group at a future point in time which would have proven very useful in isolating the cause of any anomalies.

Feedback received from participants was relatively sparse but followed common themes indicating issues that need to be approached in the tool’s design:

- **Tag Names:** Names of some objects did not clearly indicate their contents

or composition. Items in the Scopic exhibition such as ‘Foot and Mouth’ were highlighted.

- **Barcode Positioning:** The height of tags was highlighted by multiple participants, they were placed approximately 1.5 metres from the ground which caused an issue for shorter participants. This would appear to be an inherent problem with visual tagging technologies without placing multiple tags, at multiple heights.
- **Scan Failures:** Some participants experienced frustration when barcodes failed to scan the first time, average scan failure rate was 3.48 (Table 6.8) which would indicate that many participants experienced this problem.
- **Range of Object Topics:** Objects were identified as too similar due to the use of the Scopic Exhibition in the task’s learnscape. In practice it is difficult to find an area featuring diverse ranges of subjects on a university campus due to its departmental nature.
- **Clearer Directions for Recommendations:** Due to the location system used for objects it is possible to judge distance but not direction, some participants highlighted this as a failing and would like better directions to recommended objects.
- **Multimedia Content in Information Provided:** A higher degree of videos and other multimedia content was desirable in the information provided, this opinion may be due to poor recognition of audio clips in the information or a genuine desire for more visual media.
- **Sharing of Pages:** Sending pages to friends was a relatively common theme (three participants noted that it would be a desirable feature). Sharing to services such as Facebook, Flickr or the Durham University Online Learning Environment was highlighted specifically.

6.4 Summary of Results from Technical Measures

The tool allowed the monitoring of clicks through the mobile device’s internet browser. It could determine how ‘deep’ a learner’s exploration of data was - how many links into a piece of information they navigated. A clickthrough measure of ‘1’ means that the participant viewed information for the object only and did not explore the information in more depth by clicking on the hyperlinks embedded within.

Distances are displayed using aggregates of the distances between the vectors that represent the locations of objects that were scanned by participants as they progressed through the task. A distance of ‘0’ implies an object that was scanned more than once.

Metric	Min.	Max.	Median	Mode	Average	Standard Deviation
Click-through depth	1	27	1	1	2.28	5.18
Object Information Views	7	22	12	12	12.84	3.8
Scan Failures	0	9	3	3	3.48	2.38
Distance between Tags Scanned	0	0.1481	0.0114	0	0.0282	0.04
Audio Clip Clicks	0	6	2	2	1.72	1.51

Table 6.8: Summary of Results from Other Technical Measures

6.4.1 Click-through

For the most part, participants did not progress past the first page of information (i.e. information about the object itself). The average measure is buoyed up by an extremely high maximum which would be hard to explain if not for the Think-Aloud protocol in effect during the task which allowed the observation of participants clicking many links in an attempt to “test the software” or “navigate back to the starting page of information from links on subsequent pages” - creating an extremely high click-through measure with an action that did not appear to significantly aid in their construction of mental models. This anomaly is easy to observe using the median and mode measures in Table 6.8.

6.4.2 Object Views and Scan Failures

Learners construct cognitive models at a varying pace, so it was predictable that a different numbers of objects would be scanned by each participant. A relatively high maximum at 22 objects reflects learners who ‘skimmed’ through the information looking for something of interest or were perhaps already acquainted with many of the concepts involved in what they were reading. Even the minimum of seven objects implies that no participants found the scanning system completely unusable and chose to scan more than one item.

There are no significant patterns in number of object information pages viewed as show in Figure 6.3 where participants are ordered chronologically. Logically if multiple participants were learning as a group it may have been possible to observe small clusters of similar numbers of views which would indicate interaction. This figure highlights an individual aspect of the process of learning informally on a mobile device which could be related to screen size, the ability to issue one device per person or the individual nature of the way the task was structured.

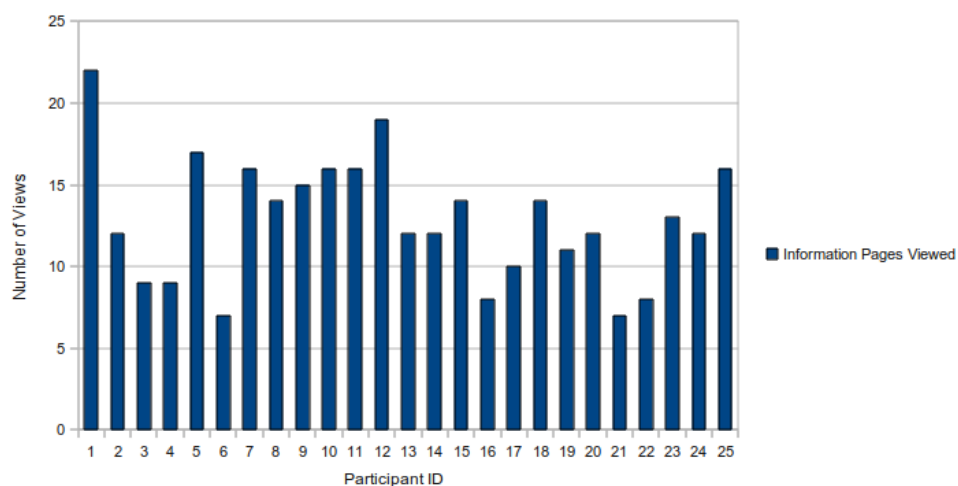


Figure 6.3: Information Views By Participant

6.4.3 Distance Between Tags Scanned

A very small average distance indicates a sequential approach to scanning by most participants which the circular physical shape of the learnscape used for the task may have perpetuated. This can also be contrasted with data in Table 6.5 to suggest that learners were not travelling large distances to view recommendations. The recommendation algorithm employed by the tool does take distance into account when providing objects that a user may be interested in which may explain this pattern, but could also indicate an opportunistic pattern that learners employed when navigating the space.

6.4.4 Audio Clip Clicks

The average figure of 1.72 audio clicks per user reflects a low uptake in this type of embedded media, results from the post-task questionnaire show a low awareness of audio clips in the information provided and these figures indicates that some but not all learners engaged with the clips provided.

6.5 Object Information Page View Summary

‘My DNA’ was an overwhelmingly popular item (Table 6.9) followed closely by significant landmarks in the learnscape such as lecture theatres (with prominent signage) and vending machines, which some participants even made use of during the experiment. The popularity of the IT Service Kiosk Computers can be explained by their presence on both sides of the circular learnscape and the relatively high proportion of those from technical disciplines who are more likely to be interested in learning more about objects such as these.

The popularity of ‘My DNA’ may be related to the object itself (it’s visual or intellectual appeal) or could be related to its physical position. The object was located within line of sight of the starting location and may have been one of the first objects that participants noticed after their brief induction.

Object	View Count
My DNA	33
Vending Machines (Calman Centre)	28
Arnold Wolfendendale Lecture Theatre	24
Cosmic catastrophes and under your skin	20
ITS Kiosk	20
Calman Centre Cafe	20
Big Bang and Rewards	19
The Tonsilrainbowlitis Virus	16
Calman Centre Reception	15
Cell from the brain of cat-woman	15
Virus and Tycho's Supernova	15
Friendly Bacteria	14
Supergiant star illuminating dust	14
Skin Cell Fighting Cancer	13
Fly Sperm and Nebula	12
Blood and The Universe	12
Electricity Planet Evolving	11
Foot and Mouth	10
Kepler and HeLa	10
Portrait of Professor Sir Kenneth Calman	9
Red Hole	9
Stomach Explosion	9
Breast Cancer Cell	8
Sweet White Blood Cell	8
Universe as a tube	8
Red Giant	8
Light Echo from Star V838	6
Puffy the artery slayer	6
Superduper Supernova	2
New New Earth	2

Table 6.9: Summary of Information Page Views, By Object Title

6.6 Recommendation Usage

The tool logged views that originated from user-clicks on the recommendation screen so that they could be differentiated from the user being in front of an object and scanning its barcode (Table 6.10).

Views from the Recommendation Screen	Views from Scanned Tags
114	367

Table 6.10: Distribution of Information Page Views: Recommendations Versus Scanned Tags

Additionally when a recommendation was selected the tool logged the position of that recommendation (Table 6.11) for analysis. The vast majority of participants

September 29, 2010

using the recommendation subsystem selected objects in the top five recommended positions. This is as predicted and could indicate that the algorithm is generating meaningful recommendations for each user. Other explanations for this pattern include those items being at the top of the object list, a simple opportunistic selection and the popularity of items 1,2,4 and 5 could be explained by the three object wide recommendation ‘grid’ that was displayed in the tool. As many members of western countries have a natural urge to start from the left, as when reading books or using a computer [73] it is logical to assume similar patterns apply to software on mobile devices, which would be reinforced by these observations.

Recommendation Position	Users who viewed object at position
1st	26
2nd	19
3rd	7
4th	14
5th	19
6th	4
7th	2
8th	0
9th	1
10th	0
11th	4
12th	2
13th	1
14th	1
15th	3
16th	1
17th	2
18th	1
19th	2
20th	2
21st	2
22nd	0
23rd	1
24th	0
25th	1

Table 6.11: Recommendations selected by users, By Position Displayed in the Tool

6.7 Detailed Analysis

6.7.1 Prior Computer Experience Versus Perceived Benefit

Participants who answered ‘agree’ or ‘strongly agree’ to Question 6 on the post-task questionnaire found the information provided informative to some degree. Figure

September 29, 2010

6.4 examines these answers against the levels of Prior Computer Usage indicated in the pre-task questionnaire to look for correlation. The number of affirmative answers to Question 3 on the pre-task questionnaire is used as an indicator of computing ability.

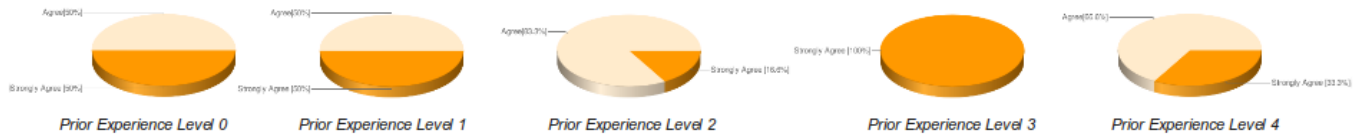


Figure 6.4: Participants rating the informativeness of the information provided by Prior Computing Experience Level

The relationship demonstrated graphically can be further illustrated via Pearson's Product Moment Correlation Co-efficient which for this set of data was $r = -0.0243$ (4sf). Next to no correlation between these two measures implies that the same amount of benefit was perceived regardless of previous computing experience which can indicate that the tool is applicable to a wider range of learners than those who are comfortable with technology.

6.8 The Study In Perspective

6.8.1 Evaluation Methods

The results and subsequent examination in this chapter have highlighted areas that could, retrospectively, have been structured differently to produce optimum results. These errors are acknowledged below, and accounted for in the conclusions of this study, which is approached in the next chapter.

- **Scan Failure Logging** was performed as an aggregate measure when in fact logging failures-to-scan on a per-object basis could have proven more effective. One item's barcode which continually failed to scan correctly may have influenced the figures shown and created an unrealistic expectation of failure rates in the barcode scanning subsystem of the tool.

- **Audio Clips** could have been made significantly more prominent in the information provided, learners would rather have been made visually aware of the clips than have them appear as standard hyperlinks. (Section 6.8.2)

6.8.2 Focus Group

Some of the failings highlighted above were approached in a semi-structured, post-study focus group involving participants who had volunteered to take part during the task. Despite a high number of volunteers only one focus group could be held due to learners' time constraints, the structure and resulting feedback from this focus group is described below.

Structure

Four participants (n=4) attended a focus group in an informal setting and in a semi-structured interview were asked:

1. Were you aware of audio clips in the tool?
2. If you saw the tags used in the study elsewhere, would you interact with them?
3. What was your strategy in selecting recommendations?

Feedback

Throughout the process a researcher made notes on recurring themes and levels of agreement within the group, the following common themes could be identified from focus group participants shown below, with some direct quotations:

- **Audio Clips:** The presence of Audio Clips was not obvious, participants who used them discovered them unexpectedly. Participants who were not aware of audio clips were interested in hearing samples of what they had missed.
- **Interested:** Participants had mentioned the technology to other learners.
- **Recommendations:** Some participants would select random recommendations to “test the software” examining the top and bottom of the tool's recommendation list for variation.

- **Tagging:** All Participants are keen to use two-dimensional barcodes again now that they “understand the technology”.

6.9 Chapter Summary

This chapter has presented the results of this study using a mixture of graphical and textual representations. Virtually all aspects of the evaluation technique utilised yielded a 100% response rate, with questions on Audio Clips in information being the notable exception (Section 6.3.5) Results have been analysed and discussed in order to allow conclusions to be reached in the following, final chapter.

Chapter 7

Conclusion

7.1 Introduction

This chapter summarises the work presented in this thesis and relates its findings to the learning outcomes developed in Chapter 1. The chapter ends with a discussion of potential future work and a brief epilogue.

7.2 Thesis Summary

The focus of this thesis was to motivate Informal Learning by using Visual Tagging, Audio Clips, Mobile Technology and a Context-Sensitive Recommendation Algorithm. Informal Learning is a valuable method of education that is often hard to utilise and track effectively, ultimately this thesis hopes to promote Informal Learning as a practice by demonstrating the *QRCode Tourist Tool* and reinforcing the various methods of providing information in a way that is interesting and applicable to learners in the analysis of this study's results.

The QRCode Tourist Tool was proposed to assist those people wishing to learn informally. The tool seeks to provide high quality information quickly and efficiently that may not normally be available to learners without a relatively large amount of searching in books, or on the internet. Additionally, as users of the tool learn the tool adapts based on their ratings, scanned objects and personal characteristics (context) and provides recommendations of other items they may wish to see in an

effort to streamline the learning process.

In Section 1.4 a set of Research Questions were established that this thesis aimed to address, the remainder of this section is dedicated to summarising the qualitative and quantitative evidence collected in support of each of these questions and the conclusions that can be drawn from it.

7.2.1 Are learners interested in the objects around them in a typical educational space?

Aim: To use a Visual Tagging system linking to high-quality information about objects to encourage learners to take an interest in their surroundings.

The *QRCode Tourist Tool* has provided learners with a means of discovering such information where previously there was none. Learners found the information aggregated from various public sources to be of significant interest and “will use it again in the future” 6.8.2. Learning in such situations was typically described in a manner that matched the definition of ‘Reactive’ learning, an opportunistic approach where learners capitalise on the presence of learning objects around them.

7.2.2 Does prior computer usage affect the benefit a learner believes they have gained from learning informally using a mobile, electronic device?

Aim: To determine whether learners who use computers regularly are more likely to find a mobile, informal learning technology useful or comprehend it faster than learners who only interact with computers irregularly.

Based on an evenly distributed number of participants in terms of prior computer usage, the vast majority of learners found the tagged objects to be interesting which indicates that degree of prior computer usage plays an imperceptible part in the usability of this tool and the ability to engage in learning informally with it as a result.

7.2.3 Does the addition of audio clips to primarily textual, on-screen information make it more interesting to learners?

Aim: To discover if embedding audio clips in information about objects makes them more interesting to learners.

A higher number of participants were unaware of Audio Clips in the information provided by the tool than any other feature (Section 6.3.5), coupled with more questionnaire answers tending towards disagree/neutral the addition of audio clips cannot be deemed a success.

It is established that a variety of media types suit different kinds of learners (Section 2.4.2). As discussed in Section 6.3.5 audio clips could have been made more obvious to learners and it is believed that this is the reason for their poor uptake, and subsequent poor ratings.

7.2.4 Based on information about a learner and objects that the learner has recently been searching for information on, can an algorithm predict other objects that the learner might be interested in?

Aim: Create a recommendation algorithm that presents learners with items that coincide with their interests based on the learner's context (personal data, location) and the actions of other learners that are deemed similar to them.

Recommendation usage was reviewed in Section 6.6 and represented almost a quarter of all information views of learners using the *QRCode Tourist Tool*. High utilisation of the top recommendations in the *top-N* list displayed to learners indicates objects that learners would find interesting were being recommended.

Without this part of the tool learners would have been able to scan objects directly in front of them but could have missed out on discovering new objects related to their interests in areas that they may not usually visit.

7.2.5 Do learners respond positively to informal learning using mobile devices by highlighting that they would travel a large distance to see more, or allow learning about designated objects to influence their schedule?

Aim: Question learners who have used the described recommendation algorithm to determine if they would change their daily routine due to recommendations received from the *QRCode Tourist* tool.

All learners indicated that they would travel to at least another location in the same building to view a recommendation. The tool produced recommendations that were accurate enough to make the vast majority state that they would travel to a different building to view a recommendation which indicates a combination of high quality recommendations and interesting learning material.

Some learners indicated they would travel to different sites within the university which is a time consuming task, the range of answers to this question (Reviewed in Table 6.5) could indicate varying motivations to learn informally. As the practice is so casual (Section 2.4.2) there will invariably be some learners who commit more, or less than others depending on their own intrinsic motivation. If encouraged as a practice by an institution extrinsic motivating factors may help Informal Learning expand quickly employing methods such as those presented in this thesis.

7.3 Future Work

The solutions presented in this thesis for motivating and improving Informal Learning, while largely successful, could be enhanced or significantly furthered by engaging in additional research. Suggestions for this research are as follows:

7.3.1 Informality of Experimentation

This thesis featured a study that placed participants in an informal environment and encouraged them to learn. Reactive learning 2.4.2 was a seemingly natural outcome although by the very act of 'placing' a participant in a learning environment

Deliberate learning may have been encouraged. Future work should seek to remove this slightly formal setting, perhaps by remote observation of participants devices and/or learning activities.

7.3.2 Variety and Availability of Tagged Items

A limited number of items were tagged in this study, due to a number of limitations around participant availability and suitable learning spaces (5.5). Future work in the same area should seek to expand the number of objects available, potentially to multiple areas and/or sites as a natural extension to the evaluation performed in this Thesis.

7.3.3 Quality of Information

Quality of information, defined as “a user criterion which has to do with excellence or in some cases truthfulness in labeling” [101] or at an ‘operational level’ information that users identify as “useful, good, current, and accurate” [87] was judged as “informative” by all participants in this study. Nevertheless creating high-quality information is a large area of research unto itself. The *QRCode Tourist* tool could be extended with peer-reviewed entries from reliable sources or live streams from online sources such as news websites.

Moreover Personalisation of data in tools such as this and in hypermedia is an on-going goal of much existing research ([78], [110], [72]) that seeks to mine data about user’s past habits and other elements of context to allow bespoke information provision leading to a richer and more applicable user experience.

7.3.4 Interconnectivity

Collaborative learning is extremely powerful (Section 2.2.2) and adding the ability to tag items collaboratively in a way that ensures a lack of duplication and tagging of only items that will be of interest to learners will allow users to chart their own course in areas that need not necessarily be restricted to a campus or small learnscape making the experience truly user-driven and informal. Semantic Annotations [56]

from learners working from their individual strengths and expertise in various topic areas, if managed correctly, will serve to strengthen the quality of object information and hence enhance the learning experience.

Bringing learners together through common interests discovered using data logged by a tool such as the one presented in this thesis can create casual interest groups that will share information for mutual benefit. Following the spirit of Informal Learning (Section 2.4.2) such recommendations should not be governed or supervised but encouraged and presented so that learners in a 'common interests group' know about one another but are allowed to engage casually, in a way that is comfortable for them.

7.3.5 Improved Tagging System

Some feedback on the tagging method selected for this study highlighted that Visual Tags are a poor selection for those of differing heights and abilities (e.g. poor sight). Research into presenting visual tagging systems in a way that made them accessible to all would be valuable - highly visible sign posting and recognition of tags from multiple angles may all serve to enhance the experience.

Visual Tagging may become obsolete with the increasing popularity of technologies such as GPS and the continuing development of the ability to sense a device's location accurately even when indoors, additionally the advent of new consumer technology such as *Google Goggles*¹ which uses an object itself as a tag may make the specially formulated graphical tag (such as the 2D Barcodes using in this thesis) obsolete.

7.3.6 Comparison Versus Model-Based Recommendation Algorithms

Deshpande and Karypis [22] describe a model-based, top-N, collaboratively-filtered recommendation algorithm. Although the user-based recommendation algorithm

¹Google Goggles: <http://www.google.com/mobile/goggles>

(Section 3.4) presented in this thesis performs well on experimental scales, model-based algorithms would scale significantly better for large numbers of learners.

Comparing a context-sensitive, user-based algorithm such as that which is presented in this work against a model-based algorithm such as the one presented in Deshpande and Karypis' work [22] which shows to have better results than traditional user-based algorithms could provide additional valuable insights into the uses and effectiveness of context in learning.

7.3.7 Interacting with Mobile Devices

As mobile devices evolve more ways to interact with objects are appearing. In the time it took to write this thesis several portable, multi-touch tablet computers have been released to consumer markets that provide many of the benefits of the mobile phones used in this study, with a significantly larger display area and better opportunities for interaction and learner involvement. As the nature of man and machine becomes more symbiotic it is imperative that research continually reassesses the ways that learners engage with the world around them and takes advantage of technologies such as Location-based Annotations [75], Peer-to-peer grids [71] and Augmented Reality [85] to stay relevant to learners needs.

7.4 Conclusion

Increasingly the internet and the constant miniaturisation and embedding of technology mean that researchers can access a wealth of data about a learner's life, location and friends. In this thesis a tool has been presented which mined this data and used it to produce a *tailored* set of recommendations that encouraged learners to expand their knowledge from the world around them.

The tagging system created as part of this study is still in place in the Calman Learning Centre at Durham University and over 120 tags have been scanned by passing students without any prompting from researchers between October 2010 and March 2010. This adds weight to these conclusions, learners want to learn outside the classroom and by empowering Informal Learning with tools such those

described it is possible to help them.

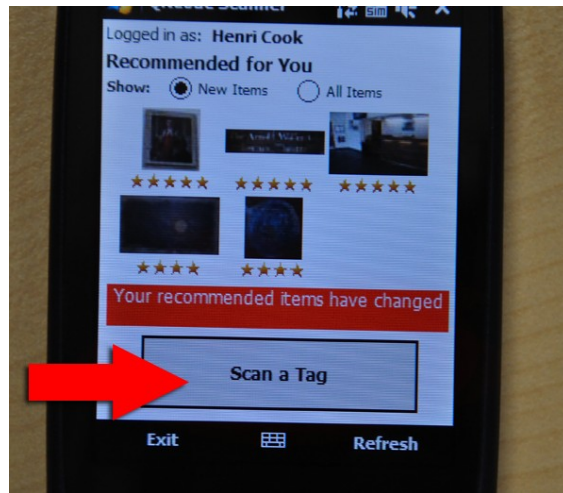
Appendix A

Case Study Materials

A.1 Graphical Instructions

Visual Tagging Evaluation Illustrated Instructions

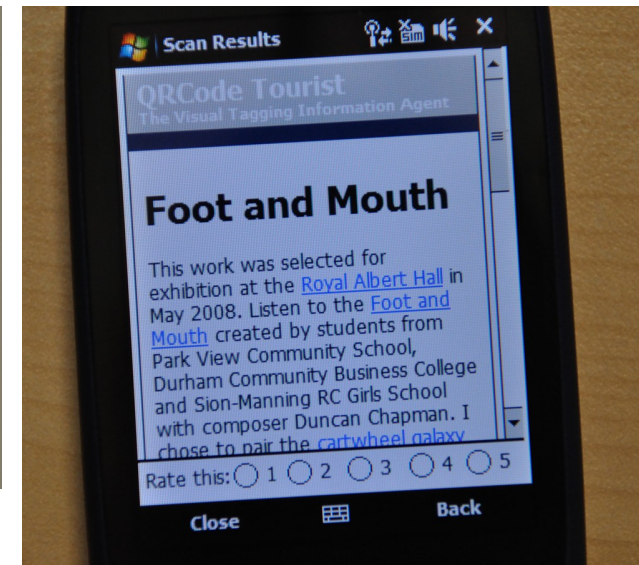
1



2



3



A.2 Written Instructions

Visual Tagging Evaluation

Experiment Instructions for Participants

Introduction

Thank you for agreeing to be part of this study to evaluate a Visual Tagging system. Please read this sheet carefully as it contains important instructions for the experiment. After reading this document you will be asked to fill out a consent form and an initial questionnaire.

Background

There are very few opportunities for students to learn autonomously outside of the lecture theatre, this study seeks to evaluate one such method of encouraging such *informal learning* by providing you with a series of objects within Durham University's Calman Centre that are visually tagged with two dimensional barcodes, E.g.



The text "This is a 2D Barcode"
expressed as a two dimensional barcode

You should have been provided with a ready-to-use mobile phone and a separate set of instructions illustrating how to use the device. Each of the 'tags' shown above can be photographed to receive information about the item they are attached to from the Internet. While viewing the information about an item you are able to rate it (and are encouraged to do so) so that the software can recommend other items that you, or others like you, might find interesting.

Task

During this experiment you should progress through the Calman Centre scanning tags that interest you, we encourage you to make full use of the system including ratings and recommendations. Please feel free to take as much time as you wish while exploring, the minimum time for the experiment is **15 minutes**.

Contacts

If you are interested in the results of this study or have any questions/concerns, you may contact Mr. Henri Cook (e-mail: h.a.cook@durham.ac.uk) at the completion of this study (October, 2009). Please note that only overall results, not individual results will be disclosed.

Thank you for your participation.



A.3 Learning Materials for the Task

Object Name	Information Provided
Arnold Wolfendendale Lecture Theatre	<p>Sir Arnold W. Wolfendendale FRS (born June 25, 1927 Rugby, Warwickshire [1]) is a British astronomer who served as Astronomer Royal from 1991 to 1995.</p> <p>Wolfendendale graduated with a BSc in Physics from the University of Manchester in 1948, followed by a PhD in 1953 and a DSc in 1970. He was elected a fellow of the Royal Astronomical Society in 1973, and a Fellow of the Royal Society in 1977. He retired from teaching in 1992 and was knighted in 1995. In 1996 he became Professor of Experimental Physics with the Royal Institution of Great Britain. A lecture theatre in Durham University's new Calman Learning Centre has been named in his honour.</p> <p>During his career he held academic posts at the universities of Manchester, Durham, Ceylon and Hong Kong, and was head of department at Durham where he remains an emeritus professor.</p>
Big Bang and Rewards	<p>The nerve cells pictured play an important role in our interactions with food, money and addictive drugs. Activated by unexpected rewards, they make a chemical called dopamine, which is believed to affect memory formation in the brain. These neurons (pictured in rat brain) die off during Parkinson's disease. Schizophrenia and manic depression often involve a dopamine disorder, which can reduce our ability to remember, pay attention and solve problems.</p> <p>How did the Universe come to look the way it does today? The Millenium simulation (pictured) uses maths to model the evolution of the Universe. The model predicts how changes in dark matter gave rise to galaxies, each one composed of stars and planets. The bright streaks shown represent the vast filaments that ramify the Universe, each made up from clusters and superclusters of thousands of galaxies containing many billions of stars.</p>
Blood and The Universe	<p>Cells are so tightly packed together in our bodies that telling one kind from another can be tricky. Scientists use fluorescent labels to tag different cells in a tissue. The coloured dots in this picture pin-point the various kinds of blood cell in a mouse spleen. Red and white cells made here help the body to fight infections. The mouse cells in this picture are reacting to a protein from a rabbit by clumping together.</p> <p>Scientists have measured the heat left over after the Big Bang to make this map of the Universe. Microwaves in the sky hold clues about how stars and galaxies formed as the Universe got bigger and cooler. A satellite called the WMAP (Wilkinson Microwave Anisotropy Probe) was sent into space by NASA to measure temperature changes. Now astronomers believe that the Universe is 13, 700 million years old.</p>
Breast Cancer Cell	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Breast Cancer Cell created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>Titan, Saturn's largest moon and a breast cancer cell are very similar. They both have a golden colour and are similar in shape. The breast cancer cell has an epicenter and the brown roots shoot out in small groups. They have the same texture and similar features such as dark patches and vain like tendrils. I thought it would be good to compare these two images because I like the way they look so alike but are so completely different.</p> <p>Saturn's largest moon is over a billion kilometers from Earth. Titan, as it is called, shimmers with golden hues. The moon's dry lake and stream beds occasionally flood with liquid methane from showers of methane rain. It took eight years for the camera that produced this image to reach Titan. While it landed on Saturn's moon, the Huygens probe sent back some images to Earth and then disappeared. This panoramic fish eye view was taken 5 kms above the moon's surface.</p>
Calman Centre Cafe	<p>This is the Calman Centre Cafe operated by the university Brand YUM. The cafe offers a range of snack foods and meals from 9am-4:30pm.</p>
Calman Centre Reception	<p>The reception at the Calman Centre acts as an information point for Visitors and Students alike. Staff are trained to deal with a wide variety with questions about the centre, the university and the local area.</p>

Cell from the brain of cat-woman	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Cell from the Brain of Catwoman created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>This magnificent image was discovered when a scan was carried out on cat-womans brain, following a fall. The nucleus in the centre could help to explain her extraordinary vision. We chose this image because it inspired us to think about vision.</p> <p>Seldom is death so beautiful than in outer space. At the core of this magnificent halo is a dying sun-like star, ten thousand times as luminous as our Sun. The outer halo looking like a splash of paint is not a feature of all nebulae. Nebulae are clouds of gas and dust where stars emerge or die. This image of the Cats eye nebula was captured by the Nordic telescope in the Canary Islands. This nebula is 3000 light years from Earth.</p>
Cosmic catastrophes and under your skin	<p>Cuts that draw blood go deeper than your top-skin. Just below are cells like the ones in the picture. They keep fairly busy making a protein called keratin that helps to protect your skin. Eventually these cells lose their DNA and end up squashed flat forming the protective top-skin. The ones pictured here have been stained with a toxin (phalloidin) from the death-cap mushroom, <i>Amanita phalloides</i>. The zoom on this microscope is x40.</p> <p>A supernova (soop-er-no-va) happens when a star blows up in the sky. This can release enough energy to outshine an entire galaxy of billions of stars. The fiery image of Simeus 147 was captured by telescopes pointed towards Taurus. The light from this cosmic catastrophe reached the Earth about 100 000 years ago. All that remains of the original star's core is a spinning neutron star that has collapsed under its own gravity.</p>
Electricity Planet Evolving	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Electricity Planet created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>The Electricity Planet has an electric zone (e-zone). This enables it to change colour every year that it is growing. This year it is the year FE49M, or blue. It is 100 light years deep, the E-zone only works when it's growing. It takes 5 years to fully grow. It's beginning its second year at the moment, so in three years it will be fully grown. The black parts are growth spurts. There is only one source of life, it is called Zykone. The red circle is another planet called Dion. It is in the universe of Electro and it orbits the Ragn. We discovered this planet and we can prove it!</p> <p>Your lungs can spread out across a tennis court and have around 1500 miles of tiny air sacs. As cells die they are replaced. Across the massive surface area of your lungs, there is considerable opportunity for the repair system to mess up. The CAT scan here pictured displays growths (top left hand side of the image) which are quite rare but can develop into cancer. Most of the time growths don't cause any harm, although airways can get blocked.</p>
Fly Sperm and Nebula	<p>Crane flies look like giant mosquitos. In the UK we call them daddy long-legs. In the USA they are called jimmy spinners or mosquito eaters, but they rarely eat mosquitos. There are 14 000 different species making them one of the largest insect groups. They feed on nectar or not at all. Most live only to mate and die as adults. Their larvae live in roots and plants, sometimes causing damage. Here pictured is a developing sperm cell from a crane fly showing threads of protein.</p> <p>A nebula is a dust cloud filled with hydrogen and charged particles of gas. A planetary nebula forms when a star dies, but stars can be born from such dust clouds too. The picture shows a nebula that is rectangular in shape. Astronomers believe this is a cylinder viewed from the side, an unusual nebula that marks the death of a star. This image was created from pictures taken at different times of year by the Hubble space telescope.</p>

Foot and Mouth	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Foot and Mouth created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>I chose to pair the cartwheel galaxy with the foot and mouth virus as I live on a farm and sadly that was infected with foot and mouth in 2001. Although I was only four I can clearly remember it. I decided to pair them together while at home watching the television, that day at school we had been shown the Scopic images we could use to pair something with. I chose the cartwheel galaxy as it looked very interesting and colourful. I chose the foot and mouth virus as I have always been interested with it, and amazingly enough they are similar.</p> <p>The Cartwheel galaxy used to be like the Milky Way until it bumped into a nearby galaxy a few hundred million years ago. Rather like a rock tossed into a pond, the impact sent ripples of gas and dust outwards at great speed. The stars are created on the crest of the waves (the outer blue ring). This image was created using four major telescopes (Chandra, Galaxy Evolution Explorer, Hubble and Spitzer) that detect different parts of the electromagnetic spectrum. The Cartwheel galaxy is 500 million light years from the Earth.</p>
Friendly Bacteria	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Friendly Bacteria created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>Titans ruled by the youngest, Cronus, who overthrew their father, Uranus, at the urgings of their mother, Gaia ('Earth') destroyed by the Olympians: a salutary reminder of the lack of permanence and intransience of the world My Bacteria is so light, and so bright twirling and spinning Just like Titan orbiting Saturn satelliting round Like a faithful dog Leashed to its master Unable to leave.</p> <p>Saturn's largest moon is over a billion kilometers from Earth. Titan, as it is called, shimmers with golden hues. The moon's dry lake and stream beds occasionally flood with liquid methane from showers of methane rain. It took eight years for the camera that produced this image to reach Titan. While it landed on Saturn's moon, the Huygens probe sent back some images to Earth and then disappeared. This panoramic fish eye view was taken 5 kms above the moon's surface.</p>
ITS Kiosk	<p>The ITS Kiosk services allows you to purchase print credits, check email, login to DUO or search the library catalogue in various convenient locations around the campus.</p> <p>For assistance you can contact: itservicesdesk@durham.ac.uk</p>
Kepler and HeLa	<p>A lady called Henrietta Lacks died about sixty years ago from cancer. Some of her cells were kept by the hospital for research. These were called 'HeLa' (Hee-La) cells after her. They divide to make new cells at a furious rate and are easy to culture in the laboratory. The cell in the picture is about to split into two. You can see a coloured cloud of chromosomes in the middle of the cell, which is about a 10th of a millimeter in size.</p> <p>When stars get old they don't always die quietly. Some create the most wonderful fireworks displays called supernovas. Kepler spotted this exploded star without even using a telescope because the bang caused it to glow so bright in the sky. The explosion sent gas and dust flying into the surrounding space at millions of miles an hour. This image was created using pictures from the three main NASA telescopes: Hubble, Spitzer and Chandra.</p>

Light Echo from Star V838	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Light Echo created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman. The colours are so shiny and it looks three dimensional. I wanted to use fluorescent colours and explore its specialness. The way stars sparkle is a huge reason why I chose this picture - it reminds me of a drop of water hitting a puddle. A light echo is the illumination of the surrounding dusty cloud structures. This effect has revealed new patterns never before seen since the star suddenly brightened in 2002 becoming 600,000 times more luminous than the sun. The echoing of light through space is similar to the echoing of sound through air. As light from the stellar explosion moves outwards so it lights up different parts of the dust. V838 is located about 20,000 light years away from the earth and is at the outer edge of our Milky Way galaxy.</p> <p>What does a chopped walnut stem look like? This highly magnified cross-section shows in detail the outer layer (epidermis) and inner tissue (cortex). The large cavities at the centre are vessels that transport sugar solution and minerals to and from the roots. The surrounding vessels transport water from the roots to the leaves. This image was taken with a scanning electron microscope.</p>
My DNA	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the My DNA created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>This is my DNA. My brother's is the same because we are identical twins. The yellow outline is the double helix which forms a spiral. It looks as if this spiral was coming out from the far bottom of the picture getting bigger and bigger as it gets to the front. It is as if I was looking down a well. I like the way me and my brother are. I like my picture the way it looks.</p> <p>The Cartwheel galaxy used to be like the Milky Way until it bumped into a nearby galaxy a few hundred million years ago. Rather like a rock tossed into a pond, the impact sent ripples of gas and dust outwards at great speed. The stars are created on the crest of the waves (the outer blue ring). This image was created using four major telescopes (Chandra, Galaxy Evolution Explorer, Hubble and Spitzer) that detect different parts of the electromagnetic spectrum. The Cartwheel galaxy is 500 million light years from the Earth.</p>
New New Earth	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the New New Earth created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>Around 500 years ago Spanish astronomer Ceanne Thompson, spotted this new planet. Planet New New Earth, it's called this because it looks like a much larger version of earth. It is seated on Orion's Belt. The vibrant blue planet is said to have no life forms yet, but humans can live there because it has the perfect temperature and cures for cancer. It is surrounded by oxygen and carbon dioxide for life forms to breath. There has been a few spottings of human figures but this could easily be large rocks. It is 16,000 light years from earth.</p> <p>Your lungs can spread out across a tennis court and have around 1500 miles of tiny air sacs. As cells die they are replaced. Across the massive surface area of your lungs, there is considerable opportunity for the repair system to mess up. The CAT scan here pictured displays growths (top left hand side of the image) which are quite rare but can develop into cancer. Most of the time growths don't cause any harm, although airways can get blocked.</p>
Portrait of Professor Sir Kenneth Calman	<p>Kenneth Calman was born on Christmas Day 1941 to Arthur McIntosh Calman and Grace Douglas Don. He was educated at the independent Allan Glen's School and went on to study Medicine at the University of Glasgow, graduating BSc, MB ChB, PhD and MD. He lectured there in Surgery before his appointment to the Chair of Clinical Oncology in 1974, and became Dean of Postgraduate Medicine in 1984.</p>

Puffy the artery slayer	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Puffy the Artery Slayer created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>This image is an Angiogram of a blocked Coronary Artery. Blockages of the Artery can be caused by fatty diets caused by genetics or Tobacco smoking-hence the title 'Puffy the Artery Slayer' (As in puffing on a cigarette). So the Angiogram of a Coronary Artery is the perfect match to its pair 'The Giant Puffball Supernova' because that caused the death of a star. (Puffy the Star Slayer).</p> <p>Over a thousand years ago a bright new object was seen in the sky. Over the course of a few days the object glowed brighter than the planet Venus. Astronomers now know this was because a star had died in a massive explosion we call a supernova. As the star died, it spat out particles at millions of miles an hour creating this huge puff ball (SN1006). Despite being 7000 light years from Earth and happening all that time ago, the consequences are till clearly visible to the naked eye.</p>
Red Giant	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Red Giant created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>My chosen image is a red giant. Towards the end of a stars life the temperature at the core starts to rise, causing the star to expand. The Helium in the star fuses with Carbon and begins to burn. Even though Red Giants are common among the stars visible to the naked eye, they are very rare in space. I chose this image because it has a similar shape to the Fertilisation Cell. It's circular; it has an irregular edge and has similar markings on the surface.</p> <p>How were you conceived? Each one of us is the result of a single event, the meeting of male and female sex cells. Fertilisation occurs when the DNA in both egg and sperm comes together, but this doesn't form a single nucleus. The nucleus of each parental cell is clearly visible in this microscopic image. Each makes a copy of their chromosomes in preparation for dividing. Here pictured is the early embryo of a mouse - the larger nucleus is from the male. DNA is blue and proteins that keep genes silent are shown in red-yellow.</p>
Red Hole	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Red Hole created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>Far away, in a galaxy not yet researched lies the Red Hole. This deadly creation has an enormous appetite. Eventually the whole universe will get gobbled up if we don't react quickly. The Red Hole will consume anything including satellites and novas although its main meal is stars. The Red Hole attracts stars with a blue magnetic force laid inside the hand. The bright red colour of the hand is thought to be fluorescent. According to satellite images we think that the stars somehow get hypnotised but await further research on this theory. The Red Hole is 87 light years wide and 172 light years long and it grows progressively, the more it consumes. We were inspired by our hand shape because we identified a hand hidden in the Red Hole's partner image the human skin cell. All over the surface of your skin are squashed keratinocytes (care-ah-tin-oh-site), cells that make the protein keratin, the stuff of your hair and nails. These cells are an important protection against the outside world. You shed them daily. Within a month your body has made a new layer. The red boundaries are cell membranes. The blue blobs are DNA in the cell nuclei.</p>
Skin Cell Fighting Cancer	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Skin Cell Fighting Cancer created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>This picture is what I imagine a cell looks like when it is being attacked by cancer. I made this picture by glueing string to the cardboard to help separate the colours then glued tissue paper on to use as a cell.</p> <p>Scientists guess that if cars were as fuel-efficient as black holes, they could travel more than a billion miles on a gallon of petrol. Black holes are invisible because their extreme gravity sucks everything in, including light. They've been noticed because they have a habit of swallowing things, which then spew out a lot of energy. Pictured here is the energy from a black hole in a galaxy (called NGC 4696) about 150 million light years away.</p>

Stomach Explosion	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Stomach Explosion created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>This is what I imagine the inside of my stomach looks like when I have eaten to a Kebab. I made this by throwing lots of powder paints and glue onto a giant sheet of perspex and photographing the reactions.</p> <p>Casseopeia (Cass-ee-o-pee-ya) is a constellation next to the Plough and Orion named after the mythological Queen of Ethiopia. Shaped as a neat W or M, formed by five bright stars, it is also home to the youngest supernova remnant - Casseopeia A. Astronomers have compared the shockwaves sent out by the explosion of the star that formed Cassiopeia A (blue streaks) to a cosmic ray pinball machine. This supernova remnant is around 10,000 light years away and was first spotted from Earth around 300 years ago.</p>
Superduper Supernova	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Super Duper created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>When I went on holiday to northern Canada, I was peering out from my window one freezing night looking at the Northern Lights when something caught my attention. At first I thought it was a firework but it got much bigger and looked much hotter. It must have been the Superduper Supernova which has rays of gas hotter than a furnace. It was caused by a dying star (only 2x bigger than Mars) which exploded and became 4x bigger than Mars. I did my image of it using paint on white paper. Then I cut it out, stuck it on black card and used pastels to make the rays of gas. Keywords: Northern Lights, supernova, dying star.</p> <p>A close relative of the hamster the Mongolian gerbil is a popular pet. Cells from gerbils are also useful research tools for studying cancer, ageing and infectious diseases. Within the tiny sacs of gerbil lungs are cells that look like the one pictured. GeLu (Jell-Ooo) cells make collagen and other materials that help cells gel together. They also nurture other lung cells that make a special liquid called surfactant, which stops lungs from collapsing.</p>
Supergiant star illuminating dust	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Supergiant Star created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>The telescopic image I chose was a supergiant star illuminating dust. the bright colours remind me of the rainbow with a wide spectrum of different shades.</p> <p>All over the surface of your skin are squashed keratinocytes (care-ah-tin-oh-site), cells that make the protein keratin, the stuff of your hair and nails. These cells are an important protection against the outside world. You shed them daily. Within a month your body has made a new layer. The red boundaries are cell membranes. The blue blobs are DNA in the cell nuclei.</p>
Sweet White Blood Cell	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Sweet White Blood Cell created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>My collage is a special white blood cell that helps to protect the body from diseases. It is in the shape of a wrapped-up sweet. It is special because you can eat as many sweets as you like and you will not be affected. The sweet white blood cell stays inside your body to fight the sugar. If you would normally go hyper eating sweets, the sweet white blood cell helps you to stay calm and sensible. I made it with collage on the inside of a chocolate box and then I cut the plastic into a sweet shape and added strips of foil over it. Keywords: cell, bacteria, sugar.</p> <p>What is a sunspot? Although darker and cooler than the rest of the Sun, the temperature of a sunspot is still hot enough to melt diamonds. Sunspots only last for a few days, but can be bigger than the Earth. This close-up shows a sunspot (darker region) surrounded by bubbles or granules on the Sun's surface. Each of these is around 1000 km wide and lasts around 10 minutes.</p>

The Tonsilrainbowlitis Virus	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Tonsilrainbowlitis Virus created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>My picture started as a mystic rose pattern. It is what I think a virus might look like for a disease called Tonsilrainbowlitis. I have had tonsillitis so I have written an acrostic poem about it.</p> <p>Throat is red and hurting. Oh, the painful small gland! Need to get some medicine. Swelling has started to disappear, Infection almost gone. Lucky me! I feel much better now.</p> <p>Did you ever wonder how many other suns there are in the Universe? In about five billion years our Sun might look a bit like this unusual cloud of gas and dust called the Spirograph nebula (IC 418). A nebula is a cloud of gas and dust in outer space where stars are born or have died. At the centre of this one is a star that has run out of nuclear fuel creating what scientists call a white dwarf. The nebula is 2000 light years away.</p>
Universe as a tube	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Universe as a Tube created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>What if the universe was a tube with a circumference of one thousand miles? Would our sky still be blue? Would be more inclined to bump into other planets? Would it be easier to determine whether there is a start and an end to the universe?</p> <p>A close relative of the hamster the Mongolian gerbil is a popular pet. Cells from gerbils are also useful research tools for studying cancer, ageing and infectious diseases. Within the tiny sacs of gerbil lungs are cells that look like the one pictured. GeLu (Jell-Ooo) cells make collagen and other materials that help cells gel together. They also nurture other lung cells that make a special liquid called surfactant, which stops lungs from collapsing.</p>
Vending Machines (Calman Centre)	<p>The university's Yum brand maintains a variety of vending machines around the campus. Vending in the Calman Centre is available when the building is open, from 8am-6pm.</p>
Virus and Tycho's Supernova	<p>This work was selected for exhibition at the Royal Albert Hall in May 2008. Listen to the Virus soundtrack created by students from Park View Community School, Durham Community Business College and Sion-Manning RC Girls School with composer Duncan Chapman.</p> <p>Viruses are much smaller than the smallest of bacteria cell. I drew this picture with only green and yellow. I created my image by randomly poking the brush with green or yellow paint and using a splattering technique.</p> <p>Around five cosmic rays pass through your head every second. Cosmic rays are high-energy particles from outer space. Exploded stars like this one - Tycho's supernova, named after the Danish astronomer that discovered it, allow scientists to study places where cosmic rays are produced. This pretty big fluffy bubble - some 7500 light years from Earth - is all gas. It is very hot - many millions of degrees Celsius. Shock waves from the exploded star travel outwards at almost ten million kms an hour.</p>

A.4 Consent Form

Consent Form

Visual Tagging Evaluation

Date: _____
ITS Username: _____

Consent Form

Thank you for volunteering to participate in this evaluation of a visual tagging system. You will be asked to participate in a flexibly timed interaction with various tagged objects within the Calman Learning Centre. You will then be asked to fill out a questionnaire about your experience. The interaction can take anything from 5-30 minutes at your discretion and we ask for no more than five minutes of your time for the final questionnaire. The researchers appreciate your candid and direct feedback at any time.

All information you give us will be kept confidential. We will only use information about you that is available to all members of the university in this experiment (college, course, year of study and department) as well as readings of your physical location while using our device. Your identity will remain confidential to the extent provided by the law. There are no direct risks to you by participating in this study. You may withdraw your participation at any time. If you have any questions or would like a full copy of the research proposal please contact Henri Cook, Department of Computer Science, Durham University, Durham DH1 3LE (h.a.cook@durham.ac.uk). Thank you.

The participant should complete the whole of this sheet himself/herself

Have you had an opportunity to ask questions and to discuss the study? [] YES [] NO

Have you received satisfactory answers to all of your questions? [] YES [] NO

Have you received enough information about the study? [] YES [] NO

Who have you spoken to? Prof/Dr/Mr/Mrs/Ms _____

Do you understand that you are free to withdraw from the study at any time and without having to give a reason for withdrawing? [] YES [] NO

I have read the procedure described above and I voluntarily agree to participate in this study and have received a copy of this description

Signed **Date**

(NAME IN BLOCK LETTERS)

A.5 Pre-Questionnaire

Pre-Session Questionnaire

Visual Tagging Evaluation

Date: _____

ITS Username: _____

1) Age Group: 18-25 26-32 33-39 40-46 47-52 52+ (please circle)

2) Please indicate your typical computer usage: Daily Weekly Monthly Never

3) Do you engage in any of the following computer-based activities (please check all that apply)?

- Mobile Internet Browsing
- Use of mobile location-based services (e.g. Google Maps)
- Application Development (Software Engineering)
- Web Development or Design

4) Based on the explanation of visual tagging supplied, have you ever used Visual Tagging software before?

Yes No

5) Please indicate your typical usage of the internet on any mobile device:

Never Rarely Occasionally Often Very Often

6) Please read and complete a consent form

A.6 Post-Questionnaire

Post-Session Questionnaire

Visual Tagging Evaluation

Date: _____
ITS Username: _____

Please take the time to rate how much you agree with each of the following statements and hand this paper back to the researcher before you leave.

Remember: All data is treated anonymously throughout the experiment (ITS usernames are not related to real names).

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
General					
The software was easy to navigate	1	2	3	4	5
The barcode scanner was easy to use	1	2	3	4	5
Barcodes were recognized quickly	1	2	3	4	5
Overall, I found the system easy to use	1	2	3	4	5
Objects					
I found the objects that were tagged to be interesting	1	2	3	4	5
Information provided about objects was informative	1	2	3	4	5
Recommendations					
The recommendations provided by the system seemed to coincide with my interests	1	2	3	4	5
Recommendations were generated quickly	1	2	3	4	5
Surroundings					
The Calman Centre was busy during the experiment	1	2	3	4	5
Audio					
I was aware of audio clips in the information provided	1	2	3	4	5
It was easy to play audio clips present in the information provided	1	2	3	4	5
Audio clips made the information more interesting	1	2	3	4	5

1. What is the furthest you would travel to view a recommended item?

- No distance
- Another location in the same building
- Another location in a different building
- Another location on a different Durham University site

2. Assuming this software is available to you everyday, when an item is recommended would you be most likely to:

- Not travel to the object at all
- Travel to it immediately
- Remember the recommended object for the next time you are in its vicinity

3. Would you be willing to be contacted to take part in a focus group after you leave today?

- Yes No

Bibliography

- [1] C.C. Aggarwal, J.L. Wolf, K.L. Wu, and P.S. Yu. Horting hatches an egg: A new graph-theoretic approach to collaborative filtering. In *Proceedings of the fifth ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 201–212. ACM, 1999.
- [2] G.W. Allport. *Pattern and growth in personality*. Holt, Rinehart and Winston, 1964.
- [3] P. Ann deWinstanley and R.A. Bjork. Successful lecturing: Presenting information in ways that engage effective processing. *New Directions for Teaching and Learning*, 89:19–31, 2002.
- [4] D.P. Ausubel, J.D. Novak, and H. Hanesian. *Educational psychology: A cognitive view*. Holt Rinehart and Winston, 1978.
- [5] F.C. Bartlett. Remembering: An experimental and social study. *Cambridge: Cambridge*, 1932.
- [6] M. Batty and P. Kyaw. Vector-based Location Finding for Context-aware Campus. In *Proceedings of the 2009 Fifth International Conference on Wireless and Mobile Communications-Volume 00*, pages 116–121. IEEE Computer Society, 2009.
- [7] Victoria Bellotti and Sara Bly. Walking away from the desktop computer: distributed collaboration and mobility in a product design team. In *CSCW '96: Proceedings of the 1996 ACM conference on Computer supported cooperative work*, pages 209–218, New York, NY, USA, 1996. ACM.

- [8] J. Biggs. *Teaching for Quality Learning at University*. Buckingham. 1999.
- [9] J.B. Biggs. The study process questionnaire (SPQ): Manual. *Hawthorn: Australian Council for Educational Research*, 1987.
- [10] M. Boekaerts and A. Minnaert. Self-regulation with respect to informal learning. *International journal of educational research*, 31(6):533–544, 1999.
- [11] J.S. Breese, D. Heckerman, C. Kadie, et al. Empirical analysis of predictive algorithms for collaborative filtering. In *Proceedings of the Fourteenth Conference on Uncertainty in Artificial Intelligence*, volume 461. San Francisco, CA, 1998.
- [12] J.S. Bruner. *Acts of meaning*. Harvard Univ Pr, 1990.
- [13] U.B. Ceipidor, C.M. Medaglia, A. Perrone, M. De Marsico, and G. Di Romano. A museum mobile game for children using QR-codes. In *Proceedings of the 8th International Conference on Interaction Design and Children*, pages 282–283. ACM New York, NY, USA, 2009.
- [14] K. Cheverst, N. Davies, K. Mitchell, and A. Friday. Experiences of developing and deploying a context-aware tourist guide: the GUIDE project. In *Proceedings of the 6th annual international conference on Mobile computing and networking*, pages 20–31. ACM New York, NY, USA, 2000.
- [15] C. Chin and D.E. Brown. Learning in Science: A Comparison of Deep and Surface Approaches. *Journal of Research in Science Teaching*, 37(2):109–138, 2000.
- [16] Carmine Ciavarella and Fabio Paternò. Design criteria for location-aware, indoor, pda applications. pages 131–144, 2003.
- [17] F. Coffield. *The necessity of informal learning*. The Policy Press, 2000.
- [18] S. Coopersmith. A method for determining types of self-esteem. *J Abnorm Psychol*, 59(1):87–94, 1959.

- [19] M.V. Covington. The motive for self-worth. *Research on motivation in education*, 1:77–113, 1984.
- [20] J. Cross. *Informal learning: Rediscovering the natural pathways that inspire innovation and performance*. Pfeiffer, 2006.
- [21] A. C. Davies. An overview of bluetooth wireless technology/sup tm/ and some competing lan standards. In *Circuits and Systems for Communications, 2002. Proceedings. ICCSC '02. 1st IEEE International Conference on*, pages 206–211, 2002.
- [22] M. Deshpande and G. Karypis. Item-based top-n recommendation algorithms. *ACM Transactions on Information Systems (TOIS)*, 22(1):143–177, 2004.
- [23] P. Dillenbourg and D. Schneider. Collaborative learning and the Internet. *Published at <http://tecfasun1.unige.ch/tecfa/tecfa-research/CMC/colla/iccai951.html>*. *ICCAI 95*, pages 10–6, 1995.
- [24] T.M. Duffy and D.J. Cunningham. Constructivism: Implications for the design and delivery of instruction. *Handbook of research for educational communications and technology*, 171, 1996.
- [25] N. Entwistle. How Students Learn: Information Processing, Intellectual Development and Confrontation. *Higher Education Bulletin*, 1975.
- [26] N. Entwistle. *Styles of learning and teaching*. Wiley New York, 1981.
- [27] N. Entwistle. Introduction: Phenomenography in Higher Education. *Higher Education Research and Development*, 16(2):127–158, 1997.
- [28] N.J. Entwistle and Dai Hounsell. *How students learn*. Institute for Research and Development in Post-Compulsory Education, University of Lancaster, 1975.
- [29] NJ Entwistle and KA Percy. Critical thinking or conformity? an investigation of the aims and outcomes of higher education. In *Research Into Higher*

- Education, 1973: Papers Presented at the Ninth Annual Conference of the Society [for Research Into Higher Education] in December 1973*, page 1. Imprint unknown, 1974.
- [30] NJ Entwistle and P. Ramsden. *Understanding Student Learning* (London, Croom Helm). 1983.
- [31] N.J. Entwistle, J.D. Wilson, J. Thompson, J. Welsh, and T. Brennan. *Degrees of excellence: the academic achievement game*. Hodder and Stoughton, 1977.
- [32] Noel J Entwistle and Paul Ramsden. *Understanding Student Learning*. Croom Helm Ltd., 1 edition, 1982.
- [33] Fredrik Espinoza, Per Persson, Anna Sandin, Hanna Nyström, Elenor Cacciato, and Markus Bylund. Geonotes: social and navigational aspects of location-based information systems. In *Proceedings of UBIComp 2001*, Atlanta, Georgia, USA, 2001.
- [34] CB Ferster. Positive reinforcement and behavioral deficits of autistic children. *Child Development*, pages 437–456, 1961.
- [35] C.B. Ferster, B.F. Skinner, Harvard University, and United States. Office of Naval Research. *Schedules of reinforcement*. Appleton-Century-Crofts New York, 1957.
- [36] G.W. Fitzmaurice. Situated information spaces and spatially aware palmtop computers. 1993.
- [37] A. Fransson. On qualitative differences in learning: IV. Effects of intrinsic motivation and extrinsic test anxiety on process and outcome. *British Journal of Educational Psychology*, 47(2):244–257, 1977.
- [38] H.W. Gellersen. EMC: environment-mediated communication. In *International Workshop on Interactive Applications of Mobile Computing (IMC98)*. Citeseer, 1998.

- [39] D. Goldberg, D. Nichols, B.M. Oki, and D. Terry. Using collaborative filtering to weave an information tapestry. *Communications of the ACM*, 35(12):70, 1992.
- [40] R.D. Goldman. Effects of a logical versus a mnemonic learning strategy on performance in two undergraduate psychology classes. *Journal of Educational Psychology*, 63(4):347–352, 1972.
- [41] D. Hamilton and M. Parlett. *Evaluation as Illumination: A New Approach to the Study of Innovative Programs*. University of Edinburgh, Centre for Research in the Educational Sciences, 1972.
- [42] T Hannay, B Lund, Joanna Scott, and Tony Hammond. Social bookmarking tools: A general review. *D-Lib Magazine*, 11(4), April 2005.
- [43] M. Hepp. Possible Ontologies: How Reality Constrains the Development of Relevant Ontologies. *IEEE Internet Computing*, 11(1):90–96, 2007.
- [44] J.L. Herlocker, J.A. Konstan, A. Borchers, and J. Riedl. An algorithmic framework for performing collaborative filtering. In *Proceedings of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval*, page 237. ACM, 1999.
- [45] J.L. Herlocker, J.A. Konstan, L.G. Terveen, and J.T. Riedl. Evaluating collaborative filtering recommender systems. *ACM Transactions on Information Systems (TOIS)*, 22(1):53, 2004.
- [46] J. Hightower and G. Borriello. Location systems for ubiquitous computing. *Computer*, pages 57–66, 2001.
- [47] W. Hill, L. Stead, M. Rosenstein, and G. Furnas. Recommending and evaluating choices in a virtual community of use. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 194–201. ACM Press/Addison-Wesley Publishing Co., 1995.
- [48] A. Hofstein and S. Rosenfeld. Bridging the gap between formal and informal science learning. *Studies in Science Education*, 28(1):87–112, 1996.

- [49] R. Jeffries, J.R. Miller, C. Wharton, and K. Uyeda. User interface evaluation in the real world: a comparison of four techniques. In *Proceedings of the SIGCHI conference on Human factors in computing systems: Reaching through technology*, pages 119–124. ACM New York, NY, USA, 1991.
- [50] T. Jeffs and M. Smith. *Informal education: conversation, democracy and learning*. Education Now Publishing Cooperative Ltd., 1999.
- [51] E. Jensen. *Teaching with the brain in mind*. Association for Supervision and Curriculum Development Alexandria, Va., 1998.
- [52] D. John and S. Wheeler. The digital classroom: harnessing technology for the future. *Interactive Learning Environments*, 17(2):197–200, 2009.
- [53] H. Kato and KT Tan. Pervasive 2D barcodes for camera phone applications. *IEEE Pervasive Computing*, 6(4):76–85, 2007.
- [54] J.E. Katz and M.A. Aakhus. *Perpetual contact: Mobile communication, private talk, public performance*. Cambridge Univ Pr, 2002.
- [55] I. Kirschenbaum and A. Wool. How to build a low-cost, extended-range RFID skimmer. In *Proceedings of the 15th USENIX Security Symposium*, pages 43–57, 2006.
- [56] A. Kiryakov, B. Popov, D. Ognyanoff, D. Manov, A. Kirilov, and M. Goranov. Semantic annotation, indexing, and retrieval. *The Semantic Web-ISWC 2003*, pages 484–499.
- [57] R. Koetter and A. Vardy. Algebraic soft decoding of reed-solomon codes, October 14 2003. US Patent 6,634,007.
- [58] J. Lazar, J. Feng, and H. Hochheiser. *Research Methods in Human-Computer Interaction*. Wiley, 2010.
- [59] G. Linden, B. Smith, and J. York. Amazon. com recommendations: Item-to-item collaborative filtering. *IEEE Internet computing*, pages 76–80, 2003.

- [60] K. Makela, S. Belt, D. Greenblatt, and J. Hakkila. Mobile interaction with visual and RFID tags: a field study on user perceptions. In *Proceedings of the SIGCHI conference on Human factors in computing systems*, pages 991–994. ACM New York, NY, USA, 2007.
- [61] J. Maness. Library 2.0 theory: Web 2.0 and its implications for libraries. (Accessed: September 2009).
- [62] V.J. Marsick and K.E. Watkins. *Informal and incidental learning in the workplace*. Routledge, 1990.
- [63] F. Marton. Phenomenography describing conceptions of the world around us. *Instructional science*, 10(2):177–200, 1981.
- [64] F. Marton and S. Booth. *Learning and Awareness*. Lawrence Erlbaum Associates, 1997.
- [65] F. Marton, D. Hounsell, and N. Entwistle. *The Experience of Learning (2nd Ed.)*. Scottish Academic Press Limited., 1997.
- [66] F. Marton and R. Saljo. On Qualitative Differences in Learning: 1–Outcome and Process. *British Journal of Educational Psychology*, 1976.
- [67] P. Massa and P. Avesani. Trust-aware collaborative filtering for recommender systems. *Lecture Notes in Computer Science*, pages 492–508, 2004.
- [68] D.R. McGee, P.R. Cohen, and L. Wu. Something from nothing: Augmenting a paper-based work practice via multimodal interaction. In *Proceedings of DARE 2000 on Designing augmented reality environments*, pages 71–80. ACM New York, NY, USA, 2000.
- [69] V. McGivney. *Informal Learning in the Community: A Trigger for Change and Development*. 1999.
- [70] J.G. McNeff. The global positioning system. *IEEE Transactions on Microwave Theory and Techniques*, 50(3):645–652, 2002.

- [71] G. Miller, S. Fels, M. Finke, W. Motz, W. Eagleston, and C. Eagleston. Mini-Diver: A Novel Mobile Media Playback Interface for Rich Video Content on an iPhone TM. *Entertainment Computing–ICEC 2009*, pages 98–109.
- [72] B. Mobasher, R. Cooley, and J. Srivastava. Automatic personalization based on Web usage mining. 2000.
- [73] J. Nielsen. *Usability engineering*. Morgan Kaufmann, 1993.
- [74] S. Nikolettseas, I. Chatzigiannakis, H. Euthimiou, A. Kinalis, A. Antoniou, and G. Mylonas. Energy efficient protocols for sensing multiple events in smart dust networks. In *In 37th Annual Simulation Symposium (ANSS 2004*, pages 15–24. IEEE Press, 2004.
- [75] Nicholas Nova. Locative media : a literature review.
- [76] UK Government (Secretary of State for Education and Employment 1998).
- [77] Reinhard Oppermann and Marcus Specht. A context-sensitive nomadic exhibition guide. In *HUC '00: Proceedings of the 2nd international symposium on Handheld and Ubiquitous Computing*, pages 127–142, London, UK, 2000. Springer-Verlag.
- [78] B. Padmanabhan, Z. Zheng, and S.O. Kimbrough. Personalization from incomplete data: what you don't know can hurt. In *Proceedings of the seventh ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 154–163. ACM, 2001.
- [79] J. Panksepp. *Affective neuroscience: The foundations of human and animal emotions*. Oxford University Press, USA, 1998.
- [80] G. Pask. Styles and strategies of learning. *British journal of educational psychology*, 46(2):128–148, 1976.
- [81] G. Pask and BCE Scott. Learning strategies and individual competence. *International Journal of Man-Machine Studies*, 4(3):217–253, 1972.

- [82] DN Perkins. Technology meets constructivism: Do they make a marriage. *Constructivism and the technology of instruction: A conversation*, page 49, 1992.
- [83] R.S. Peters. *The Concept of Motivation*. Routledge & Kegan Paul, 1958.
- [84] J. Piaget. *The psychology of intelligence*. Routledge, 2001.
- [85] J. Rekimoto and Y. Ayatsuka. CyberCode: designing augmented reality environments with visual tags. In *Proceedings of DARE 2000 on Designing augmented reality environments*, pages 1–10. ACM New York, NY, USA, 2000.
- [86] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom, and J. Riedl. GroupLens: an open architecture for collaborative filtering of netnews. In *Proceedings of the 1994 ACM conference on Computer supported cooperative work*, pages 175–186. ACM, 1994.
- [87] S.Y. Rieh. Judgment of information quality and cognitive authority in the Web. *Journal of the American Society for Information Science and Technology*, 53(2):145–161, 2002.
- [88] C.R. Rogers. *Freedom to learn: A view of what education might become*. CE Merrill Pub. Co., 1969.
- [89] M. Rohs and R. Bohn. Entry points into a smart campus environment—overview of the ETHOC system. In *Distributed Computing Systems Workshops, 2003. Proceedings. 23rd International Conference on*, pages 260–266, 2003.
- [90] M. Rohs and B. Gfeller. Using camera-equipped mobile phones for interacting with real-world objects. *Advances in Pervasive Computing*, pages 265–271, 2004.
- [91] J. Rouillard. Contextual QR Codes. In *Computing in the Global Information Technology, 2008. ICCGI'08. The Third International Multi-Conference on*, pages 50–55, 2008.

- [92] B. Sarwar, G. Karypis, J. Konstan, and J. Reidl. Item-based collaborative filtering recommendation algorithms. In *Proceedings of the 10th international conference on World Wide Web*, page 295. ACM, 2001.
- [93] M. Sharples, J. Taylor, and G. Vavoula. Towards a theory of mobile learning. *Proceedings of mLearn 2005*, 2005.
- [94] D.H. Shih, C.Y. Lin, and B. Lin. RFID tags: privacy and security aspects. *International Journal of Mobile Communications*, 3(3):214–230, 2005.
- [95] M. A. Smith, D. Davenport, H. Hwa, and T. Turner. Object auras: a mobile retail and product annotation system. In *EC '04: Proceedings of the 5th ACM conference on Electronic commerce*, pages 240–241, New York, NY, USA, 2004. ACM.
- [96] B.R. Snyder. *The hidden curriculum*. Knopf New York, 1971.
- [97] S. Sofaer. Qualitative methods: what are they and why use them? *Health Services Research*, 34(5 Pt 2):1101, 1999.
- [98] L. Steels. Collaborative tagging as distributed cognition. *Cognition Distributed: How Cognitive Technology Extends Our Minds*, page 93, 2008.
- [99] R. Stevenson. Laser Marking Matrix Codes on PCBs. *Printed Circuit Design and Manufacture*, 22(12):32, 2005.
- [100] D.J. Stipek. Motivation to learn: From theory to practice. 1993.
- [101] R.S. Taylor and M.J. Voigt. *Value added processes in information systems*. Greenwood Publishing Group Inc. Westport, CT, USA, 1986.
- [102] K. Tobin, W. Capie, and A. Bettencourt. Active teaching for higher cognitive learning in science. *International Journal of Science Education*, 10(1):17–27, 1988.
- [103] L.H. Ungar and D.P. Foster. Clustering methods for collaborative filtering. In *AAAI Workshop on Recommendation Systems*, pages 112–125, 1998.

- [104] Central Intelligence Agency (USA). *The World Factbook*. CIA, October 2009.
- [105] M.W. Van Someren, Y.F. Barnard, J.A.C. Sandberg, et al. *The Think Aloud Method: A practical guide to modelling cognitive processes*. Citeseer, 1994.
- [106] M. Weiser. Ubiquitous computing. *IEEE Computer*, 26(10):71–72, 1993.
- [107] RW White. Motivation reconsidered: The concept of competence. *Psychol Rev*, 66:297–333, 1959.
- [108] S.B. Wicker and V.K. Bhargava. *Reed-Solomon codes and their applications*. Wiley-IEEE Press, 1999.
- [109] J. Wilson. *Philosophy and educational research*. National Foundation for Educational Research in England and Wales Windsor, 1972.
- [110] P.S. Yu. Data mining and personalization technologies. In *Proceedings of the sixth international conference on database systems for advanced applications*, pages 6–13. IEEE Computer Society Washington, DC, USA, 1999.