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# Self-Reported Learning Strategies and Preferences in Health Informatics

Narjes ROHANI[a,1], Michael GALLAGHER[b], Kobi GAL[c,d], Kasia BANAS[a] and Areti MANATAKI[e]
[a] *Usher institute, University of Edinburgh, UK*
[b] *Moray House School of Education and Sport, University of Edinburgh, UK*
[c] *School of Informatics, University of Edinburgh, UK*
[d] *Dept. of Software and Information Systems Engineering, Ben-Gurion University, Israel*
[e] *School of Computer Science, University of St Andrews, UK*
ORCiD ID: Narjes Rohani https://orcid.org/0000-0003-4441-9359

**Abstract.** Despite the proliferation of educational programmes in Health Informatics (HI) worldwide, there is limited knowledge regarding students' preferences and learning strategies in HI courses. To address this gap, we conducted a study to gather and analyse data from three HI courses. Employing the Motivated Strategies for Learning Questionnaire (MSLQ) and theories of deep and surface learning, we designed a questionnaire to collect data. The analysis of students' responses indicates that machine learning emerges as one of the most interesting topics, while certain topics such as data wrangling of genomics data were more challenging for students. Students expressed a preference for sequential learning. They exhibited multimodal tendencies regarding the type of learning resources, with tendency to prefer learning resources that have more visual contents. In all three courses, learners reported using deep learning strategy rather than surface learning, yet they appear to struggle with employing organisation, elaboration, and peer learning tactics. This study provides valuable insights into HI education, offering recommendations for educators, learners, and researchers to enhance HI education.

**Keywords.** Health informatics, Learning strategy, Learning preference, Medical education

## 1. Introduction

Due to advancements in technology and the growing volume of data, medicine and health sciences have become more quantitative, leading to the emergence of the Health Informatics (HI) field [1]. Despite the urgent need to educate healthcare professionals to become proficient in data science, students find HI topics challenging and struggle to regulate their learning process [1-4].

Learners often lack sufficient knowledge about effective learning strategies to facilitate their learning of HI topics [5]. Insights into the learning experiences, preferences, and strategies of learners can help not only in designing more effective courses [6] but also in informing students about their learning strategies and providing

[1] Corresponding Author: Narjes Rohani, Usher Institute, Old Medical School, Teviot Place, Edinburgh, UK; E-mail: Narjes.Rohani@ed.ac.uk.

suggestions to help them regulate their learning more effectively [7]. The Motivated Strategies for Learning Questionnaire (MSLQ) by Pintrich *et al.* [8] is a widely used self-report instrument to explore students' learning strategies. This instrument measures various dimensions, such as cognitive and metacognitive learning strategies [8]. Another well-known learning theory has discussed the surface and deep learning strategies [9]. Surface learning typically results in superficial understanding and limited retention of information [9]. In contrast, a deep strategy involves engaging with the material deeply and motivating to understand underlying concepts and connections between ideas [9]. This theory has been utilised to uncover students' learning strategies in various disciplines, such as biology and computer science [5, 7]. However, there is no research exploring self-reported learning strategies in HI. The contribution of this study is to address this gap by asking the following RQs: 1. What topics in HI were more interesting and difficult for students? 2. What are students' self-reported learning preferences and strategies in HI?

## 2. Method

We designed a questionnaire to collect information about students' learning experiences, preferences, and strategies in three courses delivered by the University of Edinburgh: Data Science in Stratified Healthcare and Precision Medicine (DSM) [10], Introduction to Biomedical Data Science (IBDS) [11], and Data Science for Health and Biomedical Sciences (DSHB) [12]. The DSM course [10], a Massive Open Online Course (MOOC), has attracted thousands of learners worldwide with diverse academic backgrounds and degrees. Among 3,527 learners invited, it resulted in 56 responses (rate = 2%). IBDS [11], a workshop-style course allowing topic selection, was delivered to postgraduate medicine students, with 34 students enrolled and yielded 12 responses (rate = 35%). DSHB [12], designed for undergraduate students in medical and biomedical sciences, had 30 enrolled students, resulting in 11 responses (rate = 36%). A low response rate is common in such surveys of students. According to [13] a response rate of 20%–25% for populations under 500 and 5%–10% for larger populations is fairly representative. The questionnaire with close-ended questions was designed following the MSLQ [8], Entwistle, and Biggs theories [9] to cover various aspects of learning while remaining concise, comprising 22, 18, and 20 questions for DSM, IBDS, and DSHB, respectively. The questionnaire was reviewed by all authors and underwent pilot testing with a small group of 5 people to assess clarity and estimate completion time. Then, students were invited by email to participate in filling out the final version of the questionnaire, published online on the Qualtrics platform. Completion of the questionnaire was voluntary, and a gift card was offered as a reward for participation in the DSM course (see footnote 2 for a sample questionnaire).

## 3. Results

In this section, we analyse students' responses with respect to each RQ.

[2] DSM survey: https://edinburghinformatics.eu.qualtrics.com/jfe/form/SV_6llabZnEXaVgYMm

### *3.1. What topics in HI were more interesting and difficult for students?*

As shown in Figure 1, machine learning and programming topics have emerged as interesting subjects for students. Among all topics, working with genomics data seems to be more challenging than other topics.

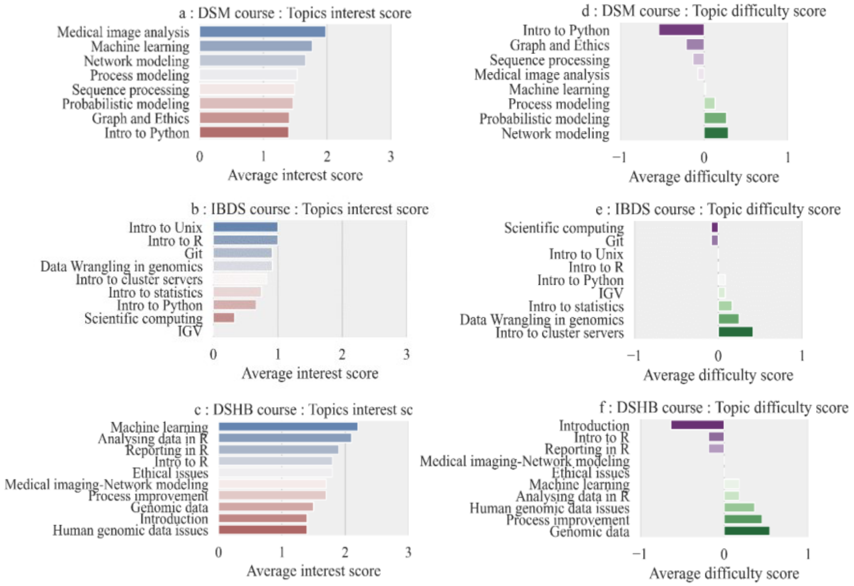


**Figure 1.** Average interest score and difficulty score of various topics in the HI courses. The values for interest level ranged from 0 to 3, indicating not interesting to strongly interesting. The values in difficulty plots range from -1 to 1, where -1 means easy and 1 means difficult.

### *3.2. What are students' self-reported learning preferences and strategies in HI?*

In all three courses, the majority of students agreed that they prefer a step-by-step and sequential approach to learning, as well as having step-by-step guidelines and teaching to follow (see **Table 1**). Regarding the type of learning resources, students have diverse preferences and would like to have a range of learning resources such as video lectures, books, and podcasts. Their first preference is visual material, indicating a preference for more visually interesting materials such as plots and flowcharts. In DSM, 83%, 11%, and 6% of learners reported visual, textual, and auditory materials as their first preference respectively. The same order appeared for the other two courses. The results also show that students prefer both hands-on experience, such as projects, and passive knowledge-acquiring activities like lectures (see **Table 1**). Students in all courses expressed that they employ rehearsal, critical thinking, and metacognitive self-regulation tactics (see **Table 1**). Among all courses, students believed that they are deep learners rather than surface learners. However, some learning tactics that indicate deep learning, such as elaboration, organisation, and peer learning, were not employed by students in all courses. For example, students in IBDS indicated that they do not use elaboration (connecting information to prior knowledge and other resources), peer learning, or organisation strategies, whereas DSM students used organisation as well as elaboration, and DSHB students used elaboration and peer learning tactics.

**Table 1.** Students reported their learning preferences and strategies for the three courses. The agreement score ranged from -2 to 2, indicating strong disagreement to strong agreement. The range for hands-on experience versus knowledge acquisition was between 0 to 10; lower values reflect a greater tendency towards hands-on experience (e.g., project) over theoretical knowledge acquisition (e.g., lecture).

| **Learning preference/strategy** | **DSM** | **IBDS** | **DSHB** |
|---|---|---|---|
| Sequential | Agree. Median score = 1 | Agree. Median score= 1 | Agree. Median score = 1 |
| Multi-modal & visual | 83% of learners agreed on visual resources as first preference. | 83% of learners agreed on visual resources as first preference. | 64% of learners agreed on visual resources as first preference. |
| Lecture vs hands-on experience | Mean score = 5.24 | Mean score = 4.08 | Mean score = 4.27 |
| Rehearsal | Agree. Median score = 1 | Agree. Median score = 1 | Agree. Median score = 1 |
| Elaboration | Agree. Median score = 1 | Disagree. Median score = - 0.5 | Agree. Median score = 1 |
| Organisation | Agree. Median score = 1 | Disagree. Median score = - 0.5 | Neutral. Median score = 0 |
| Peer learning | Neutral. Median score = 0 | Disagree. Median score = - 0.5 | Agree. Median score = 1 |
| Critical thinking | Agree. Median score = 1 | Agree. Median score = 1 | Agree. Median score = 1 |
| Meta cognitive self-regulation | Agree. Median score = 1 | Agree. Median score = 1 | Agree. Median score = 1 |
| Deep learning | Agree. Median score = 1 | Agree. Median score = 1 | Agree. Median score = 1 |
| Surface learning | Disagree. Median score = -0.33 | Disagree. Median score = -0.33 | Neutral. Median score = 0 |

## 4. Discussion

Consistent with existing literature [1, 3], machine learning and programming languages emerged as interesting subjects for students in HI. Regarding learning preferences, our findings show that students prefer sequential learning, multi-modal and visually impressive materials, and a balance between theory and practice, which is supported by previous studies [4, 6, 14]. We recommend course designers offer step-by-step teaching, incorporate diverse range of learning resources, include more visual contents, and maintain a balance between passive lectures and practical activities. Our results show that only DSHB students used the peer learning tactic. This could be due to the fact that undergraduate students are more dependent on others for learning, whereas postgraduate students like IBDS students are more independent [15]. Our previous study [4] of analysing click-stream data of the DSM course showed that students who used the peer learning tactic achieved higher grades; therefore, we suggest that teachers encourage collaboration in HI courses. The results extracted from self-reported data fairly align with the analysis of actual behaviors of students [4] and teachers' expectations, except in the case of deep and surface learning strategies. Students in all courses reported that they use deep learning strategies rather than surface learning. However, in [4], we found that the majority of students are surface learners. This contrasts with students' self-perceptions as reported in their surveys. This contradiction could be due to two reasons: first, students may have biases (e.g., due to teacher impact and social norms) in reporting their learning strategies or they may not be fully aware of their learning strategies [5]. The other reason could be due to sample bias; perhaps the students who participated voluntarily in the survey are motivated students, and surface learners who did not respond to the survey are not represented.

## 5. Conclusions

This study provided valuable insights into health informatics education. However, there are a few limitations. The first limitation is the sample size. Although we studied three courses, the number of responses is not high and might not be representative of all students enrolled in the courses. Another limitation is that self-reported information might be biased and may not accurately reflect the actual behaviour of students. Therefore, future studies should utilise both self-reported and educational data mining methods to integrate both types of data. Additionally, comparing findings based on self-reported data with the actual behaviour of students would be beneficial.

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