Learning Preferences and Strategies in Health Data Science Courses: A Systematic Review

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Abstract

Background: Teaching and learning interdisciplinary Health Informatics (HI) courses is challenging, and despite the growing interest in HI education, little is known about the learning experiences and preferences of HI students.

Objective: We conducted a systematic review to identify the learning preferences and strategies in the HI discipline.

Methods: We searched ten bibliographic databases (PUBMED, ACM, WEB of Science, Cochrane Library, Wiley, Science Direct, Springer, EBSCOhost, ERiC, and IEEE) from date of inception until June 2023. We followed the Systematic Reviews and Meta-Analyses (PRISMA) guidelines and included all types of studies that investigated the learning preferences or strategies of students in HI-related courses at any academic level.

Results: After abstract screening and full-text reviewing of the 861 papers retrieved from the databases, eight studies were selected for narrative synthesis. The majority of these papers investigated learning styles, while only one paper studied learning strategies in HI. The systematic review revealed that most HI learners prefer visual presentations as their preferred learning input. In terms of learning process and organisation, they mostly tend to follow logical, linear, and sequential steps. Moreover, they focus more on abstract information, rather than detailed and concrete information. Regarding collaboration, HI students sometimes prefer teamwork and sometimes they prefer to work alone.

Conclusions: Overall, the number of studies in this area is small. Therefore, more research needs to be done to provide insight into HI education. We provide some suggestions for conducting future research to address gaps in the literature. We also discuss implications for HI educators, and we make recommendations for HI course design.

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Learning Preferences and Strategies in Health Data Science Courses: A Systematic Review

Abstract

Background: Teaching and learning interdisciplinary Health Data Science (HDS) courses is challenging, and despite the growing interest in HDS education, little is known about the learning experiences and preferences of HDS students.
Objective: We conducted a systematic review to identify the learning preferences and strategies in the HDS discipline.
Methods: We searched ten bibliographic databases (PubMed, ACM Digital Library, Web of Science, Cochrane Library, Wiley Online Library, ScienceDirect, Springer Link, EBSCOhost, ERIC, and IEEE Xplore) from date of inception until June 2023. We followed the Systematic Reviews and Meta-Analyses (PRISMA) guidelines and included primary studies written in English that investigated the learning preferences or strategies of students in HDS-related disciplines, such as bioinformatics, at any academic level. Risk of bias was independently assessed by two screeners using the Mixed Methods Appraisal Tool (MMAT) and our study results were presented through narrative synthesis.
Results: After abstract screening and full-text reviewing of the 849 papers retrieved from the databases, eight studies, published between 2009 and 2021, were selected for narrative synthesis. The majority of these papers investigated learning preferences, while only one paper studied learning strategies in HDS. The systematic review revealed that most HDS learners prefer visual presentations as their preferred learning input. In terms of learning process and organisation, they mostly tend to follow logical, linear, and sequential steps. Moreover, they focus more on abstract information, rather than detailed and concrete information. Regarding collaboration, HDS students sometimes prefer teamwork and sometimes they prefer to work alone.
Conclusions: The studies' qualities are between 73% and 100% according to the MMAT assessment, indicating an excellent quality. However, the number of studies in this area is small and results of all the studies are based on self-reported data. Therefore, more research needs to be done to provide insight into HDS education. We provide some suggestions, such as using learning analytics and educational data mining methods for conducting future research to address gaps in the literature. We also discuss implications for HDS educators, and we make recommendations for HDS course design, for example, we recommend including visual materials, such as diagrams and videos, and offering step-by-step instructions for students.
Other: This work was supported by the Medical Research Council [grant number MR/N013166/1].

Keywords: Health data science; Bioinformatics; Learning approach; Learning preference; Learning tactic; Learning strategy; Interdisciplinary; Systematic review; Medical education

Introduction

In the era of artificial intelligence, big data and digitalisation of healthcare, there is a growing demand for educating specialists in analysing health data [1-3]. The integration of Information Technology (IT) into healthcare has undergone significant evolution in recent decades that has led to a change in the definition of health informatics. The current definition of health informatics encompasses the interdisciplinary study of designing, developing, adopting, and applying IT-based innovations in healthcare service delivery, management, and planning. In contrast, healthcare data analytics, a nascent subfield within health informatics, specifically addresses methods and techniques for analysing, integrating, and interpreting healthcare data. Health data analytics, or Health Data Science (HDS), as it can also be understood, involves data manipulation, mining, and statistical analysis to gain valuable insights from health, medical, and/or biological data. In other words, while health informatics encompasses non-computational aspects, such as system development and maintenance, healthcare data analytics or health data science concentrates only on using computational tools and methods for analysing data [4].

However, given the novel and interdisciplinary nature of health data science, learning and teaching HDS is highly challenging [1, 5, 6]. Students and teachers are often faced with a lack of common language and prior knowledge in health or computational sciences, thus making it hard to learn and teach HDS concepts effectively [7-9]. In postgraduate study, in particular, students who enrol on HDS courses have diverse academic backgrounds, including computational and medical backgrounds, but rarely a combination of the two; therefore, traditional learning and teaching approaches in biology, medicine or computer sciences may not be effective for HDS training [8, 10]. Shedding light on HDS students' learning preferences and strategies is particularly important in this context, and can help address some of these challenges [9, 11-14]. There is heterogeneous literature around the definitions of learning strategy, tactic, approach, style, and other related terms [7, 12, 15, 16]. In this paper, we view learning strategy as the approach that students use to manage their learning processes.

Similar to [17-20], we also understand learning preference as the perceived tendency of learners regarding the presentation of learning materials, types of learning activities, and the organisation of their learning process, while learning strategy/approach is the actual way in which students manage their learning process [20].

We also recognise that the learning preferences that students exhibit within the HDS field inform the strategies they undertake to support their learning [21, 22]. We decided to focus on learning preferences and strategies from the aforementioned perspectives because these field-specific preferences and strategies can offer insights into HDS education, which are useful for personalised learning [18, 23-25].

Given the aforementioned definition of learning preference, research studies about learning styles in HDS-related fields touch upon HDS-specific learning preferences and can, thus, be used to identify students' tendencies in the field regarding information presentation, learning activities, and learning organisation. However, it should be mentioned that the term "learning style" has been consistently misinterpreted [19] and defined variably across numerous studies in the literature [19, 26]. In recent years, several research studies [27, 28] have criticised the claim that each individual student has a dominant learning style, which is a stable neurological, psychological, or innate learning preference. Nonetheless, these and other studies [12, 14, 17, 19, 27, 28] have also acknowledged that students in each field of study, specific to the nature of the discipline, might exhibit some preferences regarding course materials and activities, and the way in which they approach these materials and activities [12, 14, 17, 19, 27]. As mentioned in a previous study, while the concept of stable learning styles for students is considered a myth [27], there are preferences that students exhibit within each field that informs the strategies they undertake to support their learning, which can in turn support personalised learning [13, 17, 19, 21, 27, 29-32].

Given the above, gaining knowledge about learners' preferences and strategies in HDS can help course designers create optimised courses or redesign existing courses [12, 33, 34], having a positive impact on student interest, engagement and performance [17, 34]. Additionally, informing teachers about students' learning preferences and strategies in HDS can assist them not only in selecting appropriate teaching methods but also in providing personalised feedback to students [12, 31, 35, 36].

Although several systematic reviews have been conducted to investigate the learning preferences of nurses [37, 38] and physiotherapists [39], none of them are related to interdisciplinary programmes in the realm of HDS. To fill this gap, and following the Systematic Review and Meta-Analyses (PRISMA) guidelines [40] we conducted a systematic review to present the current state of knowledge on learning strategies and preferences in HDS.

There are important aspects of learning strategies and preferences that are of interest in this systematic review because they are useful for implementing personalised learning in the HDS field [13, 22]. The type of multimedia resources in a course is important, as it significantly influences engagement, understanding, and the overall learning experience of students [41, 42]. Each discipline has its unique nature [12, 27], and presenting concepts in an effective way that is aligned with students' preferences in the discipline can improve students' satisfaction [43]. Therefore, insight into preference regarding types of multimedia used for information delivery can enhance course design and student satisfaction.

Collaborative learning is one of the popular strategies in education, but it is not always easy to implement it successfully. as engaging all students in teamwork is challenging [44-46]. Therefore, providing knowledge about students' collaboration preferences in HDS can help towards the integration of both peer learning and independent study within a course to improve collaborative skills, support diverse perspectives, and help students to develop self-directed learning skills [44-46].

Additionally, understanding whether HDS students prefer a global or sequential approach when studying topics can inform both teachers and students about effective learning strategies to enhance the student educational journey [47]. For example, course designers can arrange topics in more effective sequences that align better with students' preferences, thereby improving the overall learning experience [47].

Moreover, understanding the focus granularity preference of students, such as their inclination towards details or abstract concepts, assists in prioritising topics for teaching and determining effective teaching strategies [48, 49]. For example, identifying whether HDS students prefer applied topics or theoretical aspects helps educators decide the level of details to include in the course materials [49]. These are all important topics related to learning strategies and preferences, which are worth shedding light on in the context of HDS education.

Therefore, this systematic review focuses on the following research questions (RQs); the following RQs were selected based on available literature and their potential benefits for personalised learning [21, 22]:

1. What types of information presentation do students prefer in health data science?
2. Do students prefer team-based learning over independent learning in health data science?
3. How do students organise their learning process (global vs. sequential) in health data science?
4. Do students in health data science prefer abstract concepts over factual concepts?

Our goal with this systematic review is not only to present and analyse research findings on learning strategies and preferences in HDS, but also to discuss their implications for future course design in HDS. This way, we can help HDS educators make informed decisions about teaching methods, and assist them with developing effective courses. To the best of our knowledge, this is the first systematic review that discusses learning strategies and preferences in HDS-related disciplines. The contributions of this study are:

- Consolidate the heterogeneous knowledge available in the literature and present it in four categories, i.e., information presentation (RQ1), collaboration preference (RQ2), organisation strategy (RQ3), and focus granularity (RQ4).
- Provide suggestions to assist course designers and teachers in delivering more effective HDS-related courses.
- Provide suggestions for future research in HDS education, which can help researchers conduct better informed investigations in this area.

Methods

The systematic review was conducted to understand what learning strategies and preferences are employed by students in HDS-related fields. To answer this question, we followed all the steps outlined in the PRISMA guidelines [40] except the meta-analysis step because, given the diversity of the included papers, the narrative synthesis [50] approach was deemed more appropriate for combining the findings from the different studies. We also used the Mixed Methods Appraisal Tool (MMAT) [51] to assess the quality of the articles included. The MMAT allows to assess the quality of studies with different methodological designs, such as quantitative, qualitative, and mixed designs. The protocol used in this study is available in Multimedia Appendix 1.

Types of studies and participants

In this systematic review, we considered various types of primary studies, including both quantitative and qualitative journal/conference papers, all of which focused on exploring learning preferences or strategies in HDS-related courses. We did not apply any restrictions regarding participants' academic degrees; therefore, all high school, undergraduate, postgraduate, and non-traditional learners (e.g., healthcare professionals) were included in this study.

Study eligibility

This systematic review focuses on courses and programmes falling within the scope of HDS (employing data analytics methods to analyse biological, medical, and/or health data) [4, 9]. Studies focusing on non-data analytics aspects of health informatics were not considered in this systematic review.

The inclusion criteria are as follows:

- Language of publication: English.
- Year of publication: No restriction was applied regarding the year of publication.
- Participants: Students in fields highly relevant to HDS (using computational methods for medical/biological/health data analysis), such as bioinformatics, biostatistics, computational biology, neuroinformatics, biomedical science, precision medicine, health data science, and health data science courses.
- Participants' level: High school, undergraduate, and postgraduate students in any relevant course. Non-traditional learners, such as healthcare professionals, were also included.
- Type of publication: Conference and journal papers; primary research articles.
- Subject: Papers discussing learning preferences, strategies, tactics practices, or styles of the aforementioned learners.

- Analysis type: Both quantitative and qualitative methods were included.

Study identification

The literature search was carried out on 15th of June 2023, in which PubMed, ACM Digital Library, Web of Science, Cochrane Library, Wiley Online Library, ScienceDirect, Springer Link, EBSCOhost, ERIC, and IEEE Xplore databases were searched independently. We supplemented the literature search by employing Google Scholar manually to find potentially missed articles. Given the interdisciplinary nature of HDS, these databases were selected to cover literature across computer science, education, and medicine. We used a combination of terms to find papers about students' learning preferences and strategies in a variety of courses and programmes related to HDS. The detailed search strings are presented in Multimedia Appendix 1.

Study selection

The title, abstract, and full-text screening were carried out independently by two reviewers: NR, who has an academic background in health data science, and SS, who has a background in education. They screened the titles and abstracts of all extracted articles, followed by a full-text review of eligible studies (Cohen's Kappa agreement index = 0.95). In cases of disagreement, a third screener, AM, was involved to resolve conflicts.

Data Extraction

Both NR and SS utilised a standardised Microsoft Word form for extracting and documenting data. The data they extracted included the following categories:

- Publication characteristics: This included details such as the publication title, journal/conference, authors, and publication year.
- Methodological features: The reviewers recorded various methodological aspects, such as the participants' field and course name, the number of participants, the method of analysis employed, the type of input data used, the students' degree level, the study subject, and any learning inventory utilised.
- Learning preference/strategy: Information regarding reported learning preferences or strategies was collected, along with the corresponding percentage of students exhibiting each learning preference or strategy.

After the initial extraction, both reviewers cross-checked the extracted data to ensure accuracy. Also, both reviewers assessed the quality of the articles included independently by using the MMAT critical appraisal tool [51]. Finally, any discrepancies or inconsistencies were independently resolved by the third reviewer, AM.

Results

Search results

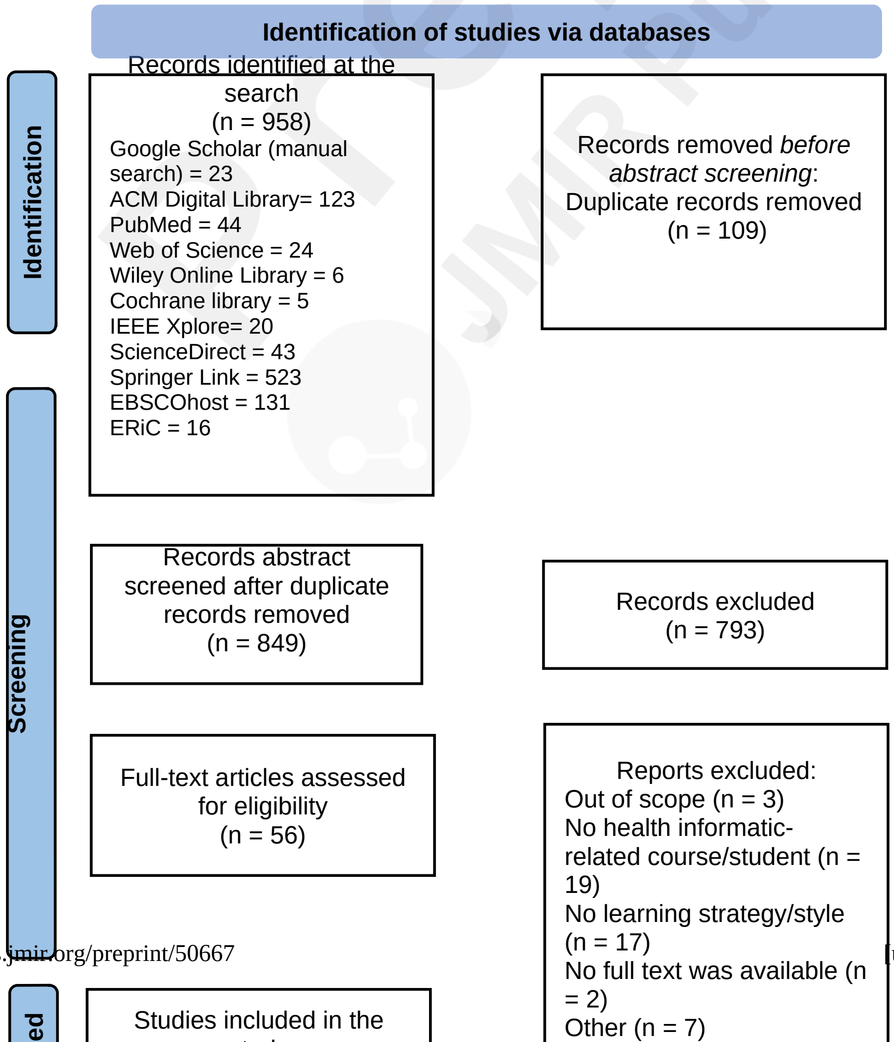
The literature search resulted in 958 articles, which were reduced to 849 after removing duplicates. More details regarding the number of papers extracted from each database are reported in Figure 1. After full text review, eight articles that were published between 2005 and 2021 were included in the synthesis step. The reasons for excluding papers during full-text screening are presented in Multimedia Appendix 1.

Characteristics of studies

As shown in Table 1, most articles (7 out of 8) were published between 2017 and 2021. The studies were conducted in the US (2), Malaysia (2), as well as Denmark, India, Sweden and Israel (1 in each). Three studies [47, 48, 56] focused on undergraduate students and another three on postgraduate students [52-54], while high school learners and healthcare professionals were each investigated by one study [43, 55].

Six [47, 48, 53-56] out of the eight included studies explored the learning strategies and preferences of bioinformatics students or courses. One study investigated a precision medicine course [43] and one study investigated an advanced statistics [52] course. It is worth noting that none of the included studies focused on courses or students specifically labelled as health data science.

The majority of the studies included (7 out of 8) are about learning preferences, while one study [16] analysed students' learning strategies. Three studies used a custom survey [43, 54, 55] to measure students' learning preferences/strategies, while the rest used learning inventories [52, 57], which are questionnaires that categorise students into different groups based on various learning dimensions (for a detailed description, please see the Multimedia Appendix 2). The Felder & Soloman Index Learning Survey (FSILS) [58, 59] was employed by three studies [47, 48, 56]; Kolb's learning style inventory [57] was used in one study [53]; and the Danish Self-Assessment Learning Styles Inventory (D-SA-LSI) based on Sternberg's theory [60-62] was applied in one study [52].



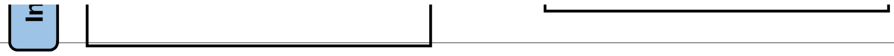


Figure 1. Flow-chart of the PRISMA selection process. Out of the 56 papers considered for full-text review after abstract screening, no full text could be found for two of them.

Table 1. Summary of the included studies.

BI: Bioinformatics, BT: Biotechnology, UG: Undergraduate, PG: Postgraduate, HCP: HealthCare Professionals. The numbers displayed in the Result column, denoted by a percentage sign, represent the percentage of learners who have declared the corresponding learning preference among all learners. Scores for Nielson and Kreiner's study indicate the strength of students' inclination toward the corresponding preference and were calculated based on D-SA-LSI (range from 0 to 7).

Study	Country	Sample size	Students' field	Course	Course delivery type	Level	Study Subject	Inventory	Result	
Holtzclaw *et al.*, 2017 [47]	US	28	Genetics	BI	Face to face with online materials	UG	Learning style	FSILS	Procession	Active = 54% Reflective = 46%
									Input	Visual = 82% Verbal = 18%
									Perception	Sensing=67% Intuitive= 33%
									Understanding	Sequential = 79% Global = 21%
Micheel *et al.*, 2017 [43]	US	751	Oncology	Precision Medicine	Online	HCP	Learning style	Custom survey with one question	Multimodal = 80%	Watching, Listening & Reading = 39% Watching & Reading = 19% Listening & Reading = 12% Watching & Listening = 10%
									Unimodal = 20%	Reading = 15% Watching = 3% Listening = 2%
Nielsen and Kreiner, 2017 [52]	Denmark	57	Public health	Advanced Statistics	Face to face	PG	Learning style	D-SA-LSI and qualitative analysis	Function	Executive= 5.42, Strong Legislative= 4.59, Strong Judicial = 4.41, Medium
									Form	Democratic= 4.62, Strong Anarchic = 4.34, Medium Monarchic = 3.68, Medium Hierarchic = 4.12, Medium

										Oligarchic = 2.65, Weak
									Learning	Conservative = 4.54, Strong Progressive = 4.83, Strong
									Level	Global = 3.97, Medium Local = 3.59, Medium
									Scope	External =5.43, Strong Internal=3.53, Medium
Diwakar *et al.*, 2018 [53]	India	84	BT, Microbiology and BI	BI and BT	Online	PG	Learning style	Kolb inventory	Assimilator= 60% Divergers= 20% Convergers= 16% Accommodator = 4%	
Ibrahim, 2020 [48]	Malaysia, Nigeria	Two datasets were used. Procession dataset: 95 Perception dataset: 2168	BI	Genomics technology	Online	UG	Learning style	FSILS and Data Mining	Procession	Active = 70% Reflective= 30%
									Perception	Intuitive = 94% Sensing = 6%
Abrahamsson and Lopez, 2021 [54]	Sweden	65	BI	BI	Online and face to face	PG	Learning style	Custom survey and qualitative analysis	Lecture Format	Real-time Zoom: 64% Offline as a Video: 27% Offline as Reading: 9%
									Synchronise Work Preference	Alone: 50% Alone & then in group:12% Same Group: 19% Different Group: 19%
Gelbart *et*	Israel	4	Biology	BI	Face to face	High	Learning	Custom	One pair Research-oriented and one pair Task-	

al., 2009 [55]					with online materials	school	strategy/approach	survey and qualitative analysis	oriented	
Li & Abdul Rahman, 2018 [56]	Malaysia	46	BI	Genomics technology	Online	UG	Learning style	FSILS and Data Mining	Procession	Active = 55% Reflective = 24% Neutral = 21%
									Input	Visual = 66% Verbal = 18% Neutral = 16%
									Perception	Sensing = 31% Intuitive =48% Neutral =21%
									Understanding	Sequential = 62% Global =12% Neutral = 26%

Regarding the analysis approach and data, most of the articles (6 studies) performed only a qualitative analysis using a questionnaire and simple quantitative methods, like statistical descriptive techniques applied to questionnaires (three of them [52, 54, 55] also supplemented their studies with a qualitative method).However, two papers [48, 56] utilised advanced data mining methods, such as k-means, and analysed log data alongside self-reported data. Nevertheless, those two studies [48, 56] did not use log data to identify students' learning preferences, but instead relied on self-reported inventories to train their models. Furthermore, the sample size of data used in all papers except [43] is less than 100 participants (Avg.: 65). The characteristics of the included articles are illustrated using various visualisations provided in Multimedia Appendix 1.
The MMAT quality scores of the included articles range from 73% to 100%, indicating a good quality overall. None of the studies were excluded based on the MMAT score. Further details regarding the quality of the included articles and MMAT checklists can be found in Multimedia Appendix 3.
We used the narrative synthesis approach [50] to combine the included studies to identify the learning preferences and strategies employed in HDS. The studies were narrated across different aspects, including information presentation preference (RQ1), collaboration preference (RQ2), preferred organisation of learning process (RQ3), and preferred focus granularity (RQ4).

Proxies used for synthesis

Due to the heterogeneity among the included studies in terms of the measurements used to determine learning preferences and strategies, we found it necessary to define specific proxies for each learning preference. These proxies help in making connections between the results presented in the different studies. Table 2 displays the proxies associated with each research question in this systematic review. More information about the learning inventories discussed in the included studies is available in Multimedia Appendix 2.

Table 2. Used proxies to connect studies' results to RQs. The supporting evidence column provides available evidence in the literature about the association between the learning preference/style/strategy and used proxies.

Learning preference/strategy	Proxy	Source of the learning preference/strategy	Supporting evidence	Research question
Watching	Visual	Customised survey designed by Micheel *et al.* [43].	Tendency towards watching lectures can be equivalent to visual preference [43].	RQ1
Lecture	Visual	Customised survey designed by Abrahamsson and Lopez [54].	Tendency towards watching lectures can be equivalent to visual preference [54].	RQ1
Assimilator	Visual	Kolb learning inventory [57].	Assimilators are interested in watching videos, and figures [57].	RQ1
Active	Teamwork	Felder & Soloman	Active students tend	RQ2

		Index Learning Survey [58, 59].	to work as a group and discuss learning materials with others [58, 59].	
External	Teamwork	Danish Self-Assessment Learning Styles Inventory (D-SA-LSI) based on Sternberg's theory [61, 62].	External students tend to work in a team and collaborate with others to solve problems [61, 62].	RQ2
Internal	Independent work	Danish Self-Assessment Learning Styles Inventory (D-SA-LSI) based on Sternberg's theory [61, 62].	Internal students prefer to work alone without communication with others [61, 62].	RQ2
Reflective	Independent work	Felder & Soloman Index Learning Survey [58, 59].	Reflective learners are inclined to work alone or communicate with a close friend instead of a large group [58, 59].	RQ2
Sequential	Sequential	Felder & Soloman Index Learning Survey [58, 59].	Sequential students have a linear learning process, which means they prefer to gain knowledge by following incremental and logical steps [58, 59].	RQ3
Assimilator	Sequential	Kolb learning inventory [57].	Assimilator students can organise the gained knowledge in a logical and clear format [57].	RQ3
Sensing	Factual information	Felder & Soloman Index Learning Survey [58, 59].	Sensing learners are interested in facts and concrete concepts. They prefer exploring detailed information and intend to solve problems with standard approaches rather than innovative ones [58, 59].	RQ4
Intuitive	Abstract information	Felder & Soloman Index Learning Survey [58, 59].	Intuitive learners are enthusiastic about abstract information, such as theories and the deep meaning of learning materials	RQ4

			[58, 59].	
Global	Abstract information	Danish Self-Assessment Learning Styles Inventory (D-SA-LSI) based on Sternberg's theory [61, 62].	Global students have the desire to solve abstract and huge problems [61, 62].	RQ4
Local	Factual information	Danish Self-Assessment Learning Styles Inventory (D-SA-LSI) based on Sternberg's theory [61, 62].	Local students prefer problems that need detailed and realistic solutions [61, 62].	RQ4
Assimilator	Abstract information	Kolb learning inventory [57].	Assimilators tend to abstract ideas and concepts and are capable of perceiving a diverse range of information [57, 63].	RQ4
Task-oriented	Factual information	Customised survey designed by Gelbert *et al.* [55].	The task-oriented student pair preferred specific tasks and they did not always stay involved in all the research steps, so they only got a basic idea of what the research was about. They concentrated more on learning the details [55].	RQ4
Research-oriented	Abstract information	Customised survey designed by Gelbert *et al.* [55].	Research-oriented students are high achievers who are highly motivated to learn concepts with a deep understanding. They focused on generating abstract ideas and explanations that were connected to theorical concepts [55].	RQ4

Information presentation preference (RQ1): Multimodal with higher tendency towards visual presentation

Among the eight studies included in this systematic review, five explored the preference of students regarding the type of presentation [43, 47, 53, 54, 56]. All of these studies reported that students in HDS-related courses prefer visual presentations and benefit more from visualisations than from audio or reading types of presentations. However, all articles also acknowledge that students are multimodal learners and do not have only one preference regarding information presentation. In other words, if students prefer visual presentations such as video watching, it does not necessarily mean that they do not have any tendency towards reading or other types of presentations [43].

For instance, Micheel et al. [43] investigated the learning styles of oncology healthcare professionals learning precision medicine from web-based educational materials. Their research study showed that 80% of the learners had multimodal learning styles. The majority of the learners (39%) preferred watching, listening, and reading, while the next largest group (19%) preferred watching and reading. Abrahamsson and Lopez [54] analysed the learning preferences of graduate students in five online bioinformatics-related courses and found that 91% of the students preferred synchronous and asynchronous lectures, which include visual presentations, while only 9% favoured reading materials. Li et al. [56] analysed the learning styles of bioinformatics students using a pre-set FSILS inventory and found that the majority of the students were visual learners (66%). Holtzclaw et al. [47] investigated the learning styles of undergraduate genetics students in a bioinformatics module and reported that the most dominant learning styles among the students was visual (82%) compared to verbal (18%). The results from these studies are consistent with other research [43, 54, 56] highlighting that the majority of students prefer visual presentations. Finally, Diwakar et al.'s study [53] found that HDS students prefer visual presentations. The authors used the Kolb learning style inventory to classify bioinformatics students into multiple learning preferences and found that the majority of learners were classified as assimilators (60%). Assimilators tend to learn visually and prefer to observe a clear explanation [57]. For a summary of the results of the studies, see the Result column in Table 1.

Collaboration preference (RQ2): Inconclusive evidence

Among all the included studies, five [47, 48, 52, 54, 56] focused on the collaboration preferences of HDS students, and the results were inconclusive, as shown in Table 1. Three studies [47, 54, 56] demonstrated that approximately half of the students preferred teamwork, while the other half preferred to work individually. Conversely, the other two studies [48, 52] indicated that HDS students had a preference for working in groups.

Holtzclaw et al. [47] is one of the studies that show no clear student preference regarding collaboration in HDS. In particular, they reported that 54% of bioinformatics students were found to be active, who typically prefer collaborating with peers, and 46% were found to be reflective, who have a tendency to work independently. The difference between the two groups was not significant enough to conclude a clear preference for collaboration or individual work. Similarly, Li et al. [56] found that over half (55%) of their undergraduate bioinformatics students were categorised as active learners (tendency to collaborate with others), with the rest being categorised as reflective learners (preference to work alone) or neutral. Abrahamsson and Lopez [54] reported that approximately 50% of bioinformatics students prefer to work alone on course assignments, while the other half prefer to work in groups (19% prefer to study with the same group for all sessions, 19% prefer to study with different groups, and 12% prefer to work individually in the first sessions and then study in groups).

Ibrahim [48] is one of the studies indicating HDS student preference for working in groups. They reported that 70% of bioinformatics students were active learners who perform better in groups. Additionally, findings from Nielsen and Kreiner's study

[52], which used the D-SA-LSA inventory, demonstrated that students enrolled in an advanced health statistics course had a strong tendency to be external, which shows their preference toward teamwork, with 89.3% of students scoring as strong or very strong in this dimension (see Table 1). This strong preference for external scope style suggests that students are willing to work as a team and communicate with others.

Overall, no consistent conclusion can be drawn based on the studies regarding HDS students' preference for working individually or in a group. Abrahamsson and Lopez [54] discuss several possible reasons for this inconsistency: First, the academic level of students may influence their preferences – postgraduate students have a higher research workload and are busier, which may lead to a higher tendency to work alone. Second, the type of assignment can influence students' working preferences. For example, the authors encouraged students to adopt paired programming for their programming assignments, and this optional approach was adopted by 85% of their bioinformatics students, highlighting the effect of including activities in course design to promote student interactions. Finally, according to the same authors, another possible reason could be the course platform, as collaboration can be difficult in online courses.

Learning process organisation preference (RQ3): Sequential learning is more popular

According to three studies [47, 53, 56], the majority of HDS learners tend to have a sequential learning preference for organising their learning process. Li et al. [56] found that 62% of their study participants had a sequential learning preference, while Holtzclaw et al. [47] reported an even higher percentage of 75% (see Table 1). Diwakar et al. [53] also supported this conclusion, with 60% of their student population being assimilators, who tend to organise information logically and with clear order [57]. We should note, however, that the number of studies that explored this dimension of preference is low, and further research is required to draw strong conclusions.

Focus granularity preference (RQ4): Higher preference towards abstract information

Five out of the eight papers included in this systematic review provide evidence regarding the focus of students on abstract versus detailed information [47, 48, 52, 53, 56], with the majority of these papers [48, 52, 53, 56] agreeing that HDS students prefer main and abstract knowledge (see Table 1 for further details).

The evidence regarding students' preferences for detailed or abstract information can be identified from the different learning styles reported (e.g., intuitive/sensory, global/local, assimilator, executive, and research/task oriented) in the learning inventories used by the five studies. Li et al.'s study [56] found that the percentage of intuitive students (48%) was higher than sensing students (about 30%), while about 20% of the students were neutral in this dimension. Intuitive students prefer to focus on abstract ideas rather than detailed and factual knowledge, and they employ a creative approach to problem-solving [58]. Similarly, Ibrahim [48] emphasised the findings from Li et al.'s study [56] and used their data in addition to Moodle data, which indicated that 94% of bioinformatics students were intuitive. In Diwakar et al.'s study [53], students were mostly assimilators (60%), who typically focus on abstract ideas and concepts. Additionally, Nielsen and Kreiner [52] showed that HDS students tend to be slightly more global (i.e., have the intention to solve abstract problems) rather than local (i.e., have the desire to address detailed and realistic problems). Even though the difference

in the average scores for the two groups is small (as shown in Table 1), a much higher percentage of students (approximately 30%) scored strongly or very strongly as global, compared to local (approximately 11%).
In contrast to the above studies that indicate a preference for abstract information, Holtzclaw et al. [47] found that most students (67%) had a preference for sensory learning, preferring to focus on factual and detailed information.
In addition to the five papers described above, Gelbart et al. [55] identified two learning approaches among high school biology students in a bioinformatics-related course: research-oriented (where abstract ideas are valued more highly) and task-oriented (where there is attention to detail and focus on factual knowledge). However, this study included only 4 participants (2 research- and 2 task-oriented), with insufficient evidence for the particular research question.

In conclusion, there is some evidence supporting the inference that HDS students prefer abstract information. However, it should be noted that there are also contradictory findings and further research is needed to arrive at a more solid conclusion.

Discussion

Eight articles that were published between 2005 and 2021 were included in the synthesis step. The synthesised results show that most HDS learners prefer visual presentations as their learning input. Regarding learning process and organisation, they mostly prefer to follow logical, linear, and sequential steps. Also, they focus more on abstract information, rather than detailed information. In terms of collaboration, HDS students prefer a mix of teamwork and independent work. Based on the findings of this systematic review, we provide here some suggestions for future research and some recommendations for improving the design of health data science courses.

Recommendations for course design

It is known that student preferences can guide course instructors in designing more effective courses [12, 23, 25]. Based on HDS students' preference for visual presentation of information, it would be beneficial to include more attractive plots, flowcharts, and visual graphics within the course materials to make them more visually impressive.
Given HDS students' inclination towards sequential learning, where they organise their learning process in logical and clear steps, it would be advantageous to consider a stepwise approach in course design. Including step-by-step instructions for practical implementations, or dividing concepts into meaningful sequential parts, may also benefit students. For example, Holtzclaw et al. [47] designed a bioinformatics module based on students' learning styles, containing highly visual components and facilitating sequential learning. Based on post-course feedback, students rated this module as valuable for their educational goals.
In terms of collaboration preferences, there is no consistent conclusion based on existing studies. Therefore, we recommend designing HDS courses in such a way that students can freely choose between individual work or teamwork. This includes coursework, where both types of assignments are offered.
Our final suggestion is that, given the evidence regarding the higher focus of HDS students on main and abstract ideas (as opposed to detailed information), and their tendency to apply a creative approach to solving problems, it would be favourable to

decrease the details in the main course materials and instead include them in an appendix. Additionally, creating challenging assignments that prompt reflection on abstract concepts and encourage the use of intuitive approaches for problem solving can be beneficial for HDS students.

Although the recommendations above are based on the preferences of the majority of students in the studies reviewed, it is essential for educators to be aware of the heterogeneity of students' learning preferences, and hence accordingly diversify HDS course design [52]. Since the suggestions presented in this systematic review are based on a limited number of available studies, it is essential for educators to carefully consider the context of their specific course and student population when integrating these suggestions into their course design.

Guidelines for future studies

Additional research is needed to explore learning preferences and strategies in health data science, especially considering the conflicting findings in certain learning preferences (e.g., collaboration preference and preferred focus granularity). In this section, we provide some suggestions for future studies.

First, we recommend the use of log data and data mining methods to analyse learning preferences and strategies in health data science. The majority of previous studies relied on self-reporting questionnaires or think-aloud protocols [43, 52, 55]. However, several studies have shown that self-reported inventories may not accurately reflect the actual behaviour of learners, as students may over- or underestimate their learning preferences/strategies [12, 64]. To avoid this bias, we suggest using log data from learning platforms and data mining methods to accurately analyse the actual behaviours of students and uncover their learning preferences and strategies [12, 65, 66]. Applying data mining tools on log data can also help to analyse the temporal and dynamic behaviour of students over time [67]. Recent studies [12, 68] have demonstrated that utilising data mining tools uncovers students' preferences or strategies, which are dynamic and highly correlated with their performance [69]. As students may change their learning preferences and strategies throughout their interaction with a course [12, 70], it is important to shed light on such changes. Currently, only two studies [48, 56] in this review have used data-driven methods, which, however, were not well designed, as they did not identify students' learning preferences based on the log data. Instead, they applied the FSILS learning inventory to identify students' learning styles and then used the identified learning styles based on self-reported data as labels to train a model using log data. For example, Li et al. [56] only trained a computational model based on self-reported data instead of finding students' learning preferences using an unsupervised approach.

Second, it is necessary to analyse larger samples to strengthen the results and increase the generalisability of findings. As mentioned earlier, all existing studies except Micheel et al. [43] analysed courses with fewer than 100 learners, which can be a limitation depending on the type of analysis conducted .. The sample size in Gelbart et al.'s [55] study is only two pairs of students. Although the study used qualitative analysis, the number of students considered, and the information reported about them appear insufficient to support their conclusion regarding the learning approaches of students. Therefore, researchers, depending on the type of analysis (quantitative or qualitative), should be aware of the importance of having suitable sample size to minimise the risk of bias in their conclusions [71, 72].

Third, most existing studies did not report the demographic information of students. This is an important omission, as students' nationality, race, and culture may affect their learning preferences [56]. To minimise the impact of other factors on the students' preferences and capture the preferences related solely to the HDS discipline, future research needs to include a diverse range of learners in terms of nationality, race, and other demographic characteristics. It is worth mentioning that in this systematic review we examined learning strategies and preferences of students across different academic levels, but no statistically significant differences were found between the different levels. Nevertheless, it is important to note that students' academic level may influence their learning strategies and preferences. This aspect requires further investigation in future studies.

Finally, future studies should focus on students' learning strategies rather than learning styles, as learning strategies are known to provide more useful information about a field in comparison with learning styles [7, 12, 73]. Also, previous research has shown that learning strategies are highly associated with students' academic performance [74, 75], while the association between learning styles and performance is controversial [73, 76]. Among the included studies, only one study [55] discussed the learning strategies of HDS students, which was limited to self-reported data and a very small sample size. Overall, much more needs to be done to gain comprehensive knowledge about HDS students. We encourage researchers to explore learning strategies in HDS using both log and self-reported data.

Limitations

A limitation of this systematic review concerns the small number of studies included (8 articles). Even though we were systematic with reviewing and synthesising these 8 articles, we acknowledge that it is a small number of studies, and therefore the results should be interpreted with caution.

Secondly, the heterogeneity among the available studies required the use of proxies to synthesise results, and using meta-analysis was impossible due to the diverse measurements utilised across the studies included. Although this systematic review defined meaningful and valid proxies to connect the heterogeneous pieces of evidence in the literature, the use of different inventories in the included studies to measure learning preferences and strategies can affect the accuracy of our findings.

It is worth mentioning that none of the studies identified labelled their course as health data science; the majority referred to them as bioinformatics courses. It is important to note that in this systematic review, health data science is defined as a discipline in which students employ computational methods and tools to analyse biological, health, or medical data. We did not include courses that focus on non-data analytics aspects, such as mobile health or electronic health records. Therefore, the findings of this systematic review may not apply to non-data analytics courses in health informatics.

Regarding search query and inclusion criteria, our study only included English primary research studies published in journal and conference formats. Also, due to the wide range of terminologies used in literature to describe learning preferences and strategies, some relevant studies might have been overlooked given the search keywords employed in this review. For example, we did not utilise the keyword "learning approach" in our search query, which could have resulted in additional studies to include.

Moreover, due to the high occurrence of false positives in the search results obtained through Springer Link and Wiley Online Library, our query for those two databases was restricted to studies including the 'student' keyword in their abstracts, which can lead to overlooking studies involving healthcare professionals.

Regarding the quality of included studies, while MMAT serves as a powerful tool with low bias in assessment [77], it should be acknowledged that the assessment of the quality of included papers can be subjective. The three reviewers, who assessed the quality of the included articles, have different academic backgrounds and levels of expertise, which can potentially mitigate the associated bias.

Lastly, students' learning preferences and strategies can be influenced by the mode of course delivery (e.g., online or face-to-face) and course design [12]; therefore, teachers and course designers should not solely rely on this study findings without considering other factors that might influence students' learning strategies and preferences. Also, some suggestions within this review may specifically apply to online courses. For instance, the recommendation of utilising learning analytics to analyse students' learning behaviour to identify dynamic learning strategies is not feasible for face-to-face courses.

Conclusions

We reviewed the literature to identify student learning preferences and strategies in health data science courses. The PRISMA guideline was employed and as a result, eight papers were included for narrative synthesis. The synthesis of these studies provided evidence that most HDS students are visual and prefer watching videos, diagrams, plots, etc. as part of their learning. They also tend to follow logical and sequential steps in their learning process, and they are inclined to focus more on abstract information rather than factual and detailed information. Moreover, there is no agreement among existing studies regarding students' collaboration preferences (teamwork vs. independent work). HDS students might prefer to work alone on some assignments while sometimes they prefer to work as part of a team.

Based on the studies reviewed, we recommend including more visual and less detailed materials in HDS courses, accompanied by stepwise instructions.

Furthermore, to address the limitations of existing studies, future research should consider using log data instead of self-reported questionnaires, so as to capture the actual HDS learning experience. Including a large sample of students from different backgrounds and races can also strengthen research results and reduce the impact of other co-factors unrelated to the HDS discipline.

Additionally, analysing the learning strategies of students instead of learning preferences has the potential to bring deep insights into HDS education, as learning strategies are more associated with student performance. Overall, since a small number of studies have investigated learning preferences and strategies in HDS, further research is needed to draw rigid conclusions.

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Authors' Contributions

NR and AM conceptualised and designed the project. NR and SS screened and reviewed the papers, while AM served as the third screener to resolve any conflicts between the two screeners. NR synthesised and wrote the first draft of the paper, and AM and SS assisted in enhancing the written work. AM supervised this project. All the authors have read and approved the final version of the paper.

Data availability statements

All data generated or analysed during this study are included in this published article and its supplementary information files.

Conflicts of Interest

None declared.

Abbreviations

BI: Bioinformatics
BT: Biotechnology
D-SA-LSI: Danish Self-Assessment Learning Styles Inventory
IT: Information Technology
FSILS: Felder & Soloman Index Learning Survey
HCP: Healthcare Professionals
HDS: Health Data Science
MMAT: Mixed Methods Appraisal Tool
PG: Postgraduate
PRISMA: Systematic Reviews and Meta-analyses
RQ: Research Question
UG: Undergraduate

Supplementary Information

Multimedia Appendix 1: Study protocol, search queries, excluded and included studies, and characteristics of the included studies.
Multimedia Appendix 2: Summary of learning inventories used by included studies.
Multimedia Appendix 3: MMAT checklist result, showing quality of the studies included.

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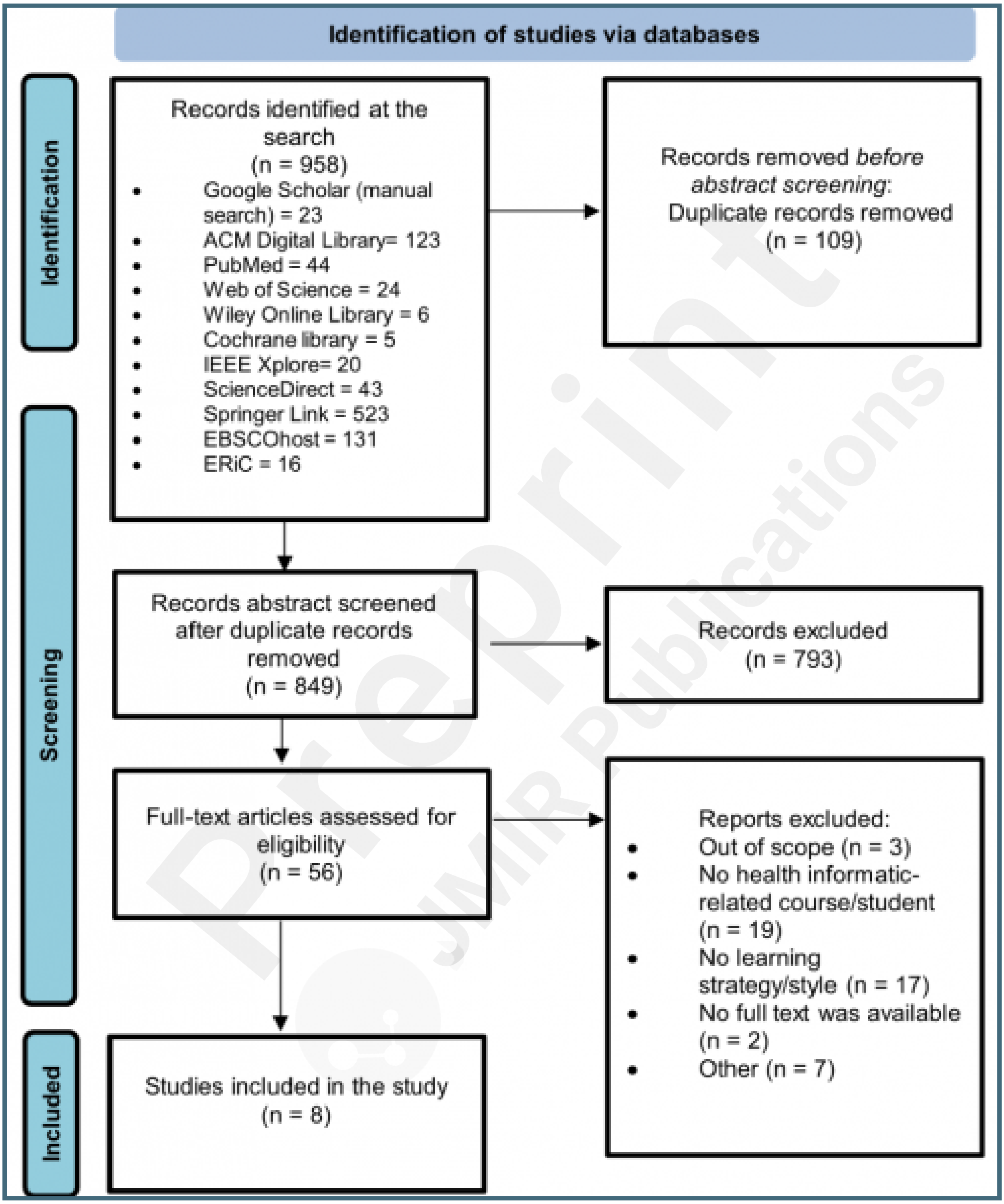
Supplementary Files

Figures

Flow-chart of the PRISMA selection process. Out of the 56 papers considered for full-text review after abstract screening, no full text could be found for two of them.



Multimedia Appendixes

Study protocol, Search queries, PRISMA check lists, and Excluded papers with reason of exclusion.
URL: http://asset.jmir.pub/assets/271604d879b919ded4976516172b1eb3.docx

Explanation of learning inventories used in the literature.
URL: http://asset.jmir.pub/assets/cde7cfade5d4d2f97f62e2dc7ea70a59.pdf

Quality assessment of the included articles.
URL: http://asset.jmir.pub/assets/ce2a13034ff9eb2e9e6b799b4d7a7a09.xlsx

TOC/Feature image for homepages

Learning Preferences and Strategies in Health Informatics Courses: A Systematic Review.