

“There’s no way to keep up!”: Diverse Motivations and Challenges Faced by Informal Learners of ML

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Abstract—In recent years, more people from different backgrounds are trying to informally learn Machine Learning (ML) using a plethora of online resources, yet we know little about their motivations and learning strategies. We carried out interviews with 22 informal learners of ML from diverse job roles and backgrounds, including Computer Science, Medicine, Finance, and others, to understand their approaches, preferences, and challenges in locating and interacting with different resources to manage their learning. We analyzed our findings using the framework of self-directed learning and found that these informal learners struggled in all stages of self-direction, including identifying learning goals and selecting resources, and that their challenges were most acute in the last stage of gauging progress and evaluating outcomes. We identify several opportunities for future research to better understand and support informal learners of ML (and other complex technical skills). In particular, there is a need to foster more self-monitoring and self-reflection techniques that can help informal learners become more self-aware and effective in directing their learning.

Index Terms—informal learning, learning ML, self-directed learning

I. INTRODUCTION

Advancements in Machine Learning (ML) are increasingly changing the nature of many work processes [1, 2]. Professional ML specialists usually have formal training in computer science (CS) or applied math. However, in recent years a growing number of non-ML specialists such as scientists [3, 4], web developers [5], UX designers [6], hobbyists, artists, and other creative practitioners [7] are informally learning ML to apply it to their respective domains. As ML solutions are being sought in areas ranging from medicine to journalism, the population of *informal learners of ML* will continue to grow [8]. ML already ranks amongst the most sought-after tech skills, with ML-related MOOCs seeing some of the highest enrollments [9, 10].

Although there is no single definition of informal learning [11], it is generally a process in which the onus of making choices about learning goals, resources, and strategies is on the learner, as opposed to teacher-led formal learning in the classroom [12]. Informal learners of ML have the opportunity to learn on-demand and access explanations and examples of various ML concepts through the wealth of materials available online [13]. But getting access to resources does not

necessarily translate to effective learning, as shown by prior work on informal learners of other technical topics [14]–[16]. As advocated by tenets of *learner-centered design* [17], we argue that to empower informal learners of ML to be the most successful, we first need to better understand their motivations, learning strategies, and challenges.

In this paper, we tackle three related research questions: 1) What motivates informal learners from different backgrounds to pursue ML? 2) What learning strategies do they use? and, 3) What challenges do they face in applying those learning strategies? We took a qualitative approach and interviewed 22 informal learners (7 women) with training in a range of fields, including CS, Engineering, Math, Medicine, Finance, Linguistics, and Anthropology. They had diverse reasons for learning ML, such as wanting to use it for medical understanding, sports data analysis, sign language translation, as well as various projects for career growth. Most did not work in ML-specific job roles but were still interested in writing ML code. Prior work has shown how non-specialist ML stakeholders benefit from such exercises to better critique ML systems and formulate advocacy arguments [18]. Our work aligns with this ongoing research agenda of increasing AI literacy for empowering stakeholders and non-specialist learners of ML by drawing the focus on current learning practices.

To understand and interpret our interview findings, we used the metacognitive lens of *self-directed learning* [19] and its three-stage model (Figure 1). We found that our interviewees’ self-directed approach was often opportunistic and narrowly focused on immediate task-based goals, with little attention to strategizing systematic approaches and learning strategies. While our interviewees struggled to some extent in all three stages (see Figure 1), our findings indicate that the challenges in gauging progress were the most acute. Learners tended to omit evaluating learning outcomes, which led to feelings of dissatisfaction, unpreparedness, and a sense that “*there’s no way to keep up!*” In particular, we found that informal learners mainly from non-CS/Engineering backgrounds struggled with setting suitable learning objectives due to the interdisciplinary and fast-paced nature of the ML field.

Based on our findings, we draw several implications for

future research in Human-Computer Interaction (HCI) to better support informal learners of ML (and similar technical skills) in becoming more self-directed. Although some recent work has been exploring self-direction in the context of learning programming [20], ML is inherently different as it requires additional skills in handling high-volume data, complex models, interactions between code and data, and some mathematical fluency [5, 21]. As such, we need to better understand the unique strategies of informal learners of ML and how they are able to set and achieve their learning goals. For example, one approach may be to further study the specific contexts of informal strategies among successful ML learners and draw upon HCI’s progress with self-tracking and self-monitoring technologies (e.g., in health and productivity domains) to support struggling learners in identifying personal metrics of progress; that can lead to developing personally-relevant strategies to achieve learning goals. Given the ascent of remote online learning during the pandemic and growing interest in upskilling and reskilling in an ever-changing modern workplace, addressing the challenges of self-directed learning will be a pressing goal in the coming years.

Our paper makes the following contributions:

- 1) Empirical insights into the background, motivation, and learning strategies of informal learners of ML.
- 2) Synthesis of key challenges that informal learners of ML face, through the lens of self-directed learning.
- 3) Design opportunities for interventions tailored to informal learners to support their self-direction through self-monitoring and self-reflection techniques.

II. RELATED WORK

Our work builds upon research on improving access to ML, informal learners of ML, and self-directed learning.

A. Improving Access to ML Literacy

As ML-driven systems are increasingly being incorporated into our personal devices and societal structures (e.g., law enforcement, financial sectors, surveillance systems) [22]–[24], there has been a growing call in the research community to support the developers, end-users, and other stakeholders of ML systems [25]–[29]. For example, recent studies have explored how to improve AI literacy among *non-expert stakeholders* of machine-learned systems through the use of interactive, *transparent*, example-based interfaces [25, 29], how the use of personally relevant data might help in better grounding self-advocacy arguments against harmful models [18] and how children make sense of AI models [30, 31].

Researchers have also categorized challenges faced by technical professionals (e.g., software developers, ML experts) [5, 28, 32], such as the interpretability of models developed by data scientists for hypothesis generation and stakeholder communication [33]. Others have studied the process of ML development (e.g., data iterations, ML diagnosis) carried out by ML-practitioners to introduce interventions to support it [28, 34, 35]. These efforts towards understanding how people build ML systems have opened up more questions about the

processes people use for learning ML. In our research, we call attention to the needs of the growing number of informal learners from domains beyond CS who are interested in learning ML, but may not necessarily be ML practitioners [36].

B. Informal Learners of Programming and ML

The concept of informal learning has been around for decades, but the definition of informal learning can be varied and encompasses several facets of learning. Some researchers describe informal learning as a paradigm where an institution sets the learning objectives and places the onus of determining the means for achieving those objectives on the learner [12]. Other researchers prefer a broader meaning where the learning is intentional, but unorganized and may be “self-directed, family-directed or socially-directed” [11].

A study similar to ours surveyed web developers learning to use a specific ML framework and found barriers to conceptual and theory learning [5]. In contrast, our work takes a qualitative approach, using the lens of self-direction to uncover broader metacognitive challenges while informally learning ML that pertains to learners’ decisions about selecting resources, uses of learning strategies, and methods of gauging progress and evaluating outcomes.

C. Metacognition and Self-Directed Learning

Knowles describes self-direction as a “systematic process” where an individual takes the initiative in diagnosing their learning needs and goals, the human and material resources needed to achieve them, choosing appropriate strategies and evaluating learning outcomes [19]. Effective self-direction requires metacognitive control where learners take charge of their own process through 1) identifying learning needs and goals, 2) choosing learning strategies, and 3) evaluating outcomes to better prepare for subsequent attempts [19]. The terms informal learning and self-directed learning are sometimes used interchangeably. In our work, we use the definition of self-direction provided by Knowles as a lens to understand to what extent people learning ML through informal means are able to self-direct their learning by strategically guiding their own metacognitive processes.

Systematic use of metacognition through self-monitoring and self-regulation have long been associated with higher academic success [20, 37, 38]. Despite the progress in (semi-)formal settings, research on how informal learners use metacognitive techniques while engaging with online learning content is limited [39]. Past research has shown that informal learners take the liberty to choose how to meet their learning needs [12, 40, 41], but also that they may prefer “trial and error” type approaches [42]. Given that metacognition can be complicated and time-consuming, there is a clear need to understand these processes in the informal learning context as a first step towards improving them, which our study explores within the context of ML.

III. METHODS

To address our research questions, we used a qualitative approach that would allow us to capture the nuances of individ-

TABLE I
 BACKGROUNDS OF INTERVIEWEES AND EXAMPLE PROJECTS THEY WORKED ON WHILE LEARNING ML.

ID (gender)	Degree (area)	Example project	ID (gender)	Degree (area)	Example project
P01 (F)	M.D. (Biology)	Pain Management Studies	P12 (M)	B.S. (CS)	Stock Market Prediction
P02 (M)	Ph.D. (CS)	Book Recommendation System	P13 (M)	B.E. (Electronics)	Sports Data Analysis
P03 (M)	B.E. (Mechanical)	Game Development	P14 (M)	M.S. (CS)	Unemployment index prediction
P04 (M)	B.A. (Finance)	Time Series Analysis	P15 (M)	B.S. (CS)	Document image classification
P05 (F)	M.S. (CS)	Sign Language Detection	P16 (F)	M.S. (CS)	Face Detection
P06 (M)	B.E. (Electronics)	Medical Image Analysis	P17 (M)	M.D. (Biology)	(None yet)
P07 (M)	B.S. (CS)	Safe path prediction	P18 (M)	M.E. (Manufacturing)	Ecommerce
P08 (F)	B.S. (CS)	Virtual Reality	P19 (M)	M.E. (Aerospace)	Social Media Content Analysis
P09 (F)	M.S. (CS)	Chatbot for Learning	P20 (M)	Ph.D. (Chemistry)	Financial Time Series Analysis
P10 (F)	B.S. (IT)	Introductory ML classes	P21 (M)	B.S. (Linguistics)	Language Translation
P11 (F)	M.S. (CS)	Business/Customer Analytics	P22 (M)	B.A. (Anthropology)	Stock Market Prediction

ual experiences [43, 44] and better understand learners’ backgrounds, motivations, strategies, struggles and workarounds. We conducted in-depth semi-structured interviews with 22 participants who had attempted to learn different technical aspects of ML (e.g., theory, implementation) on their own.

A. Recruiting Informal Learners of ML

To recruit interviewees, we used an online screener survey to gather a general understanding of the backgrounds of informal learners of ML. Our survey consisted of demographic questions about education, gender, location, age, current occupational role, and familiarity with different ML frameworks and development tools.

To ensure our survey reached a diverse population of learners, we targeted users of informal online resources [16] rather than formal university-based ML courses. These informal learning resources included forums such as subreddits (r/learnmachinelearning), popular ML tutorial sites such as MachineLearningMastery and similar Medium posts, videos on Youtube by individuals and several channels including Google Developers, FreeCodeCamp, Simplilearn, and Edureka. We also advertised the survey through our personal contacts in industry and academia. The survey respondents were offered a chance to win USD 50 in a raffle. We hosted the survey for two months and collected responses from 28 different countries with respondents from Asia (46.4%), North America (30.4%), South America (14.4%), and Europe (6.4%).

We received 126 completed survey responses, where about a quarter of respondents (24.6%) identified as female, most (86.5%) had at least one university degree, and all were between the ages of 18-34. Many respondents (45.0%) came from non-CS (non-computer-science) majors, including Business, Chemistry, Economics, Education, Engineering, Law, Management, Math, and Psychology.

Out of these screener survey respondents, 35 expressed an interest in being interviewed, and we selected 22 people (7 women) to interview. Our selection criteria were to maximize diversity in both demographics and job roles (e.g., software developers, data scientists, faculty, research assistants).

B. Semi-structured Interview Protocol

Each interview was conducted remotely using Zoom video conferencing and lasted approximately an hour. All interviewees were offered USD 15 gift-cards for their participation.

Our semi-structured interview questions focused on understanding each learner’s motivations (e.g., why they were learning ML) and eliciting details about their learning strategies (e.g., how they were learning ML). We asked the interviewees about how they planned their learning approach and how they selected resources on their own. Next, we used the critical incident technique [45] to ask questions about how the interviewees carried out their learning, focusing on examples of any critical roadblocks they faced and what workaround strategies they adopted (if any). We asked interviewees how they tested their comprehension of ML concepts (if at all). We also asked them to compare their learning experiences in ML with their classroom learning experiences in other subject areas. For example, we probed into skills or learning strategies from other domains that they were able to transfer to ML and any difficulties they faced along the way. We ended by asking them to reflect on their achievements during their learning experience, for example sharing their criteria of success and to what extent they felt they achieved success.

C. Data Analysis and Presentation

The 22 interviews were video and/or audio recorded with the interviewees’ consent and later transcribed. Two researchers were involved in analyzing the qualitative data from the interviews. We used an inductive analysis approach [46] beginning with open-coding and a quote-by-quote strategy to inspect each transcript. Our analysis was guided by the principles of self-directed learning [19] and we considered how interviewees’ responses were related to the different stages of self-direction. We assigned multiple codes to responses where necessary and had regular discussions within the research team to reconcile our final coding scheme. Following this step, we performed axial coding and also used affinity diagrams to explore themes related to our main research questions around motivations and learning strategies of informal learners of ML.

In Sections IV–VII that follow, we report on the diverse motivations of these interviewees and the challenges they faced in self-directing their learning of ML theory and practice. While several of these challenges (section VI-A, VI-B, VII-B) may apply more broadly to learners in other domains, we highlight challenges that were unique to ML in sections V-A, V-B, and VII-A.

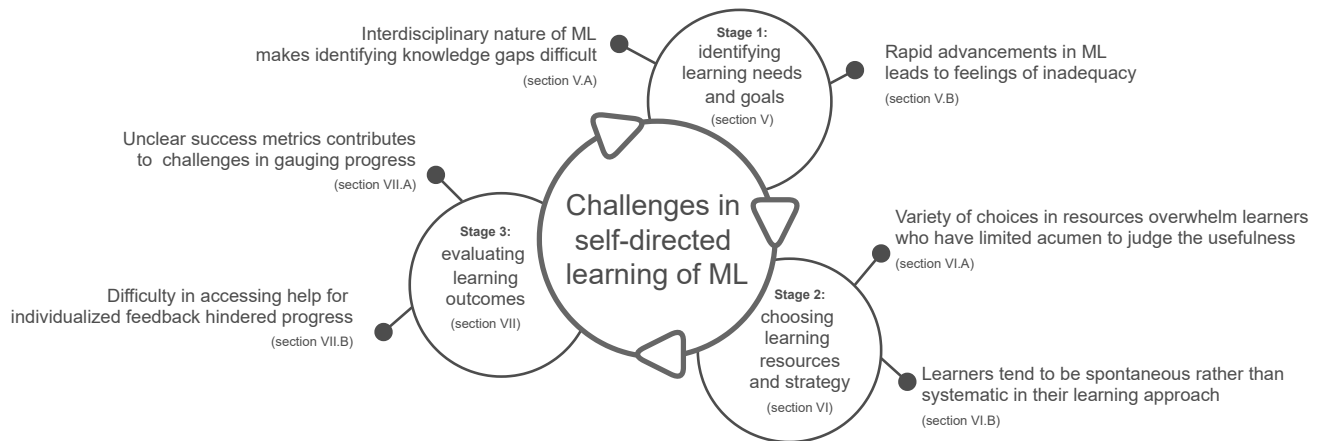


Fig. 1. We interviewed 22 informal learners of ML (machine learning) and categorized the challenges they reported according to the three stages of self-directed learning [19]: identifying learning needs and goals, choosing learning resources and strategies, and evaluating outcomes to prepare for future attempts

IV. DIVERSE MOTIVATIONS FOR LEARNING ML

Table I shows that our interviewees came from diverse educational and professional backgrounds, ranging from CS to applied Engineering fields such as Aerospace, Manufacturing, Mechanical and Electronics. Others came from non-CS/Engineering fields such as Math, Chemistry, Medicine, Finance, Anthropology, and Linguistics. They were representative of screener survey respondents and included researchers, technical educators, software developers, and data analysts, among others. In addition, these interviewees expressed diverse motivations, ranging from personal curiosity and aspirations for future job prospects to keeping up with advancements in the field, similar to prior studies of informal learners of technical concepts [5, 15, 47].

We saw a great diversity in the array of projects that our interviewees were attempting to build while learning ML. For example, among those who already had some prerequisite knowledge (e.g., math, programming, or an application domain), seven interviewees wanted to use ML skills for “pet projects.” These ranged from social causes, such as language translation for their local community, to self-development, such as personal sports data analysis. One of our interviewees, P20, who had a PhD in chemistry, described how he was making his learning relevant to a personal interest in finance: “I’m at that time in my life where I should be investing [financially]. So [financial time series analysis] felt like an applicable area.” P20 also shared how he often took a math-based approach, such as learning “dimensionality reduction by doing the math for it” and watching derivations being worked out in online lectures. Three other interviewees with math backgrounds were similarly motivated to understand the derivations of mathematical formulae that underlie ML.

Others were motivated to create a working piece of ML-powered software. For example, P21, a linguist who had no prior background in programming, shared that he had decided to develop an application for sentiment analysis as a proof-of-concept. P21 acknowledged that setting himself a concrete

goal to develop a prototype was an “accidental” decision that enabled him to make progress towards the larger goal of automating language translation. One-third of all interviewees (7/22) mentioned that implementing a working prototype by following a tutorial-based “step-by-step” process was their preferred approach.

In contrast, seven interviewees from non-CS backgrounds were motivated to learn ML as a hobby and thus did not begin with a specific project in mind. For example, P17, who was trained as a physician, expressed that he was “interested in machine learning and in [its application to] medicine.” P17’s approach to learning ML was by completing online course certifications, similar to the approach in medical training, therefore he wanted to “complete the probability course [...] and this other statistics course [...] And on the side, [complete] a linear algebra [course]” to ultimately implement “something like a ‘Hello World.’” P17 used the “Hello World” analogy from introductory programming to describe producing a first result in an ML project. This process in ML seemed convoluted to him without knowing the underlying mathematical theory.

Lastly, three interviewees were educators who were motivated to help software developers skill-up in ML. Their approach was based on studying a variety of examples. For example, P09 mentioned how she learned ML concepts on-demand by trying to teach it in a way that is “accessible to everybody.” In every session, P09 used “different examples [and went to] GitHub for additional projects.”

V. CHALLENGES IN IDENTIFYING LEARNING GOALS

According to the principles of self-directed learning, learners first have to identify their learning needs and goals [19]. We found this to be a key challenge experienced by our interviewees as they struggled to identify the ML-specific topics they needed to study. They usually lacked an adequate understanding of the problem domain and the underlying data, or lacked knowledge of relevant mathematical models, or did not have the necessary implementation skills. Additionally, the

dynamic, fast-evolving nature of the ML field compounded the difficulties in setting clear learning objectives, even for the more technical interviewees.

A. Dealing with Interdisciplinary Nature of ML

The interdisciplinary nature of ML added a layer of complexity for many of our interviewees in diagnosing knowledge gaps, especially when they lacked one or more of the prerequisite skills while leveraging different ML learning resources.

More than half of the interviewees (13/22) struggled to familiarize themselves with different areas of knowledge within ML, such as math, programming, data processing, signal processing, software engineering, and application domains (e.g., linguistics, medicine). For instance, P17 (a medical professional) describes his thoughts during his initial attempts at learning ML: *“I just decided that this was beyond me [...] And I dropped out [of the course] because I just knew that I couldn’t do it. I didn’t actually test that.”* He had subsequently given up on ML before picking it up again years later to invest time in acquiring some foundational knowledge. A contrasting approach was taken by interviewee P07, which was to *“skip that [conceptual] part, Google stuff and hack it.”*

Due to the interdisciplinary nature of ML, it was possible to have different points of entry for self-guided learning, focusing on either the implementation or theory. For example, P07’s rationale for choosing an implementation-first approach over learning theory was based on his apprehensions that focusing on theories would prevent him from *“building anything new, other than the assignments”* and consume *“a lot of time to [...] start doing some stuff.”* On the other hand, for some of our interviewees, implementation-only approaches turned out to be rather frustrating. P01 described how *“just look[ing] at the code and just implement[ing] the formula in the course to complete the task”* without first understanding *“what the formula is about or how they come up with a special mathematical formula”* made it difficult to reason about the output she observed. In such cases, interviewees preferred a more theory-first approach, focusing on *“probability and linear algebra”* even though that was, according to P17, *“a little off the track of getting something produced.”*

Our interviewees revealed yet another perspective for approaching learning ML: by first learning about ways of working with data, attempting to understand the nature of datasets, and performing descriptive statistics and visualizations. For example, P20 realized that before diving into ML, *“the most important thing is collecting data.”* He further explained his experience: *“So, I’ve been trying to write a script to pull data down and create a data structure to hold all that...I’ve actually kind of been diverting from ML and going into something ancillary to it...rather than looking at algorithms.”* (P20).

We also observed that our interviewees were struggling to strike a balance between learning programming *“to get at least a foundation”* and learning theory to *“understand what was going on behind the scenes”* to get to the point where they could read available open-source projects or code examples and *“edit it to [their] own needs”*. P21, further pointed out

how he needed to rely on his Linguistics domain knowledge to steer the development of the ML models for better outcomes:

It was suggested that we use a standard text classification algorithm [...] we needed it to take every single utterance without remembering any of the previous stuff [...] and I wouldn’t have been able to get that sort of input if I didn’t have that background in linguistics. (P21)

B. Keeping up with Fast-paced Changes in ML

One of the goals of self-directed learning is to enhance the ability of individuals to become successful lifelong learners [19]. We asked our interviewees how their experience of learning ML compared with other technical topics they may have learned, and one recurring theme was that the constant change and rapid advances in the field of ML made it difficult to keep up. Even three out of our six more technically-experienced interviewees (e.g., those from CS backgrounds) faced bouts of imposter syndrome [48] while learning ML. They expected to always stay abreast with recent developments, failing which they developed a fear that their current knowledge was inadequate. P21 explained how it was *“really rough [...] when TensorFlow was updated to TensorFlow 2.0”* because he felt like he was *“giving up this stuff that [he] worked really hard to learn.”*

In addition to keeping up with learning new ML programming tools, our interviewees also needed to stay current with ML techniques. As ML techniques evolve, so do the possible use-cases. This poses a unique challenge to the learners of ML to rapidly adapt their mental models of possible tasks and useful applications. For example, P22 shared that while it was important to make efforts to learn about the new modelling techniques and highlighted the value of *“dissecting, as you’re actually doing the actual project and not trying to find time after it’s over”*, there was little to no time available to do so *“because it’s a moving target.”* The software developers in our study often prioritized their pursuits based on time-sensitive deliverables and sometimes compromised on gaining deeper understanding, thus leading to feelings of falling behind. P16’s narrative further highlights a common sentiment among interviewees:

I don’t know as much as I would like to know because the field is always changing, especially with deep learning, computer vision, and natural language processing [...] I feel like there’s no way I can keep up with everything. (P16)

Although other computing domains, such as web development, also go through fast-paced changes, our interviewees felt that it was more challenging to keep up with ML, as developments could be happening on multiple fronts, such as, data availability, predictive models, and implementation frameworks.

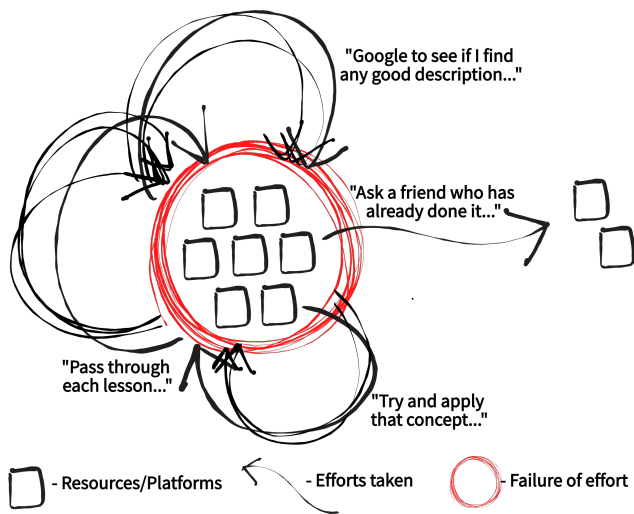


Fig. 2. Illustrates how P08 juggled between seven different resources without having any clear learning gains. P08 was able to eventually resolve her roadblock and select two specific resources by reaching out to a friend who had some experience with ML.

VI. CHALLENGES IN CHOOSING LEARNING RESOURCES AND STRATEGY

In the second stage of self-directed learning, learners seek the resources that will help them achieve their learning objectives [19]. We observed that our interviewees struggled at this stage because they were dealing with “too many choices” and often lacked a clear strategy for approaching their learning.

A. Down the Rabbit Hole: Difficulty in Choosing Resources

Due to the fast-paced, dynamic nature of the field (as seen in Section V-B), our interviewees pointed out that there seems to be a proliferation of ML-related learning materials. The explosion of choices in learning resources across multiple media types (e.g., blogs, videos, online courses) often left them feeling overwhelmed and “at sea” [49].

Although our interviewees had access to online courses which were “credible sources” of information that offered some “structure and guidance”, these learners faced challenges in selecting courses appropriate for their specific needs. According to P06, part of the challenge arose from the lack of critical awareness to “distinguish between [courses] which just want to sell you something and those that want you to learn in a more structured way.” This lack of awareness often led to interviewees who were inexperienced in CS or math to go down, what P04 describes as, a “rabbit-hole”. He explained: “I was doing sporadic tutorials but later took courses to go through the [math] step by step [...] and then that led [me] to another place. Hopping from one course to another [...] made me realize I wasn’t understanding much.”

Figure 2 shows a typical cycle of going down a rabbit hole by alternating between web searches, asking a friend, and reading various online resources, as explained by P08.

B. Lack of a Systematic Approach to Learn ML

For effective self-direction, learners should be able to strategize their approach according to their learning goals [19]. For example, a learner may employ a number of strategies to assess difficulty, decompose the problem, design solutions, manage time and resources to learn new information, and engage in practice, self-assessments and reflection [20, 38].

Among all of our interviewees, only five described a specific learning approach that helped them achieve their learning goals. While two of the interviewees (P06, P14) preferred the traditional approach of learning ML that focuses on understanding the theories and math, the others (P15, P19, P20) took a more hands-on approach of learning concepts through implementation. P15, a software engineer, described how he used a combination of “bottom up” and “top down” approaches to learn the fundamentals first, “but within two or three weeks [...], started building a [proof of concept] application [...] and [got] into the details of each component.”

In contrast, among the other 17 interviewees, we noticed a tendency to pursue learning spontaneously and a lack of clarity in formulating and articulating a systematic approach. For example, P09, who was learning ML on-the-job, described how she used a combination of library resources, online courses, and training resources at work and somewhat randomly went through different ML topics. Using this approach for over six months, P09 admitted that she failed to make progress as per her expectations and had wasted a lot of time and effort. Furthermore, when interviewees mentioned having a preference for a particular learning approach from prior experience (as described in section IV), they expressed difficulties adhering to and staying consistent in their practices for various reasons such as distraction and exhaustion. For example, P17 preferred pursuing certifications similar to his training in Medicine, but it was difficult for him to learn ML systematically as it demanded a new way of thinking, and having to deal with unfamiliar vocabulary. He often lost focus and digressed from the topic he was studying because he kept finding “too many interesting topics” which seemed like “shiny objects” that he should follow:

In the context of diagonalization [...] I find someone saying that the ‘similarity’ relationship represents a ‘change of basis’. I have been exposed to ‘change of basis’ sometime ago, but now I can follow up on this to connect these two ideas. In this example, ‘orthogonality’ is [what] I am interested in. (P17)

Another interviewee, P13 who was learning about the application of ML in the context of social media and advertisements, tried to brush up on his programming skills and ML concepts at the same time by taking courses. With his programming course, P13 did not experience much success: “I got too confused with classes and OOP concepts [in Python], because it is slightly different from JavaScript, so I dropped out.” Despite attempting to follow systematic approaches offered by courses, P13 struggled to formulate a suitable structure for his specific learning conditions and needs: “I was doing two

things at one time, whereas I should've just focused on one course [and made time] for hands-on [practice].” Four other interviewees confirmed similar struggles with prioritizing their time and selection of learning resources.

VII. CHALLENGES IN EVALUATING OUTCOMES

The final stage of self-directed learning involves evaluating outcomes of learning strategies, through self-reflection or feedback [19]. We found that evaluating learning outcomes came across as the most challenging aspect of self-directed learning for our interviewees. Many reported lacking a strategy to gauge their own progress, while some others experienced difficulties in reaching out for feedback.

A. Lack of Strategy in Gauging Progress

Unlike a learner in the classroom, an informal learner may not have a predetermined rubric for self-evaluation, or a mentor to help them strategize their learning path [11]. When we probed our interviewees to define their criteria for success and what they considered an evidence of progress, we found out that the aspect of gauging progress was largely ignored. Relatedly, interviewees rarely shared any thoughts about improving their own learning strategies. Any moments of insight that may have occurred when implementing ML projects were difficult to capture and use for self-reflections.

Aligned with findings from prior studies, our interviewees' experiences with learning were opportunistic and focused on obtaining immediate results through trial and error [50]–[52]. Most of our interviewees (18/22) reported that they rarely spent any time thinking about their learning techniques or what was not working well. In fact, they only reflected on some fundamental questions for the first time when prompted during our interview. For example, P09, who had spent over a year working with natural language processing for the development of a chatbot, shared that she had “*never thought about what was a good resource.*” She further confessed that “*I am not aware [of useful resources] even now.*” Interviewees indicated that when they were pressed for time and juggling other responsibilities, they were “*not even trying to gauge anything*” and their efforts were directed to “*just get [it] done.*”

We probed into the difficulties in gauging progress and found that it was hard to even recognize progression in learning, which tended to be mostly focused on the output of their machine learning models. Interviewees mentioned feeling worried and disappointed because there was a long interval between starting coding and seeing its outcomes, which made immediate feedback difficult to obtain. Moreover, the result of an ML project may be suboptimal even if implemented correctly. The result-oriented success criteria combined with the absence of a method for observing progress hindered our interviewees from forming achievable milestones. P21 expressed that gauging progress while learning ML “*caused a lot of stress*”, partly because of his lack of technical training:

If I had known [...] what sort of path was normal, I could have set some pretty doable milestones. The milestones that I set for myself [...] tended to be

centered around completing a project, or doing a publication [...], but those are big goals. (P21)

When we inquired about what constituted moments of learning, our interviewees revealed that their learning approach tended to be somewhat eclectic, making it hard to recall specific moments of insight. For example, P22 said building an ML app was such an iterative process that even while working with a well-resourced team, it was still a struggle to capture reflections and realizations that occurred between “*the 50 other things that they tried that didn't work.*” He went on to add that, “*we do take notes [...] but [...] questions keep coming up because people forget that they've been looked at before [...] saves a lot of cycles if you can capture that correctly.*”

While our interviewees believed a systematic way of stepping through the learning experience would have been desirable, a lack of clear metrics for success and the lack of a way to observe their learning processes deterred learners from taking better control of their learning. Furthermore, our interviewees' typical methods of gauging progress, such as obtaining accurate output while programming, seemed to be unsuitable when results from ML models were suboptimal. These findings suggest that alternative methods of progress tracking could be useful in the context of ML.

B. Challenges in Seeking Help and Feedback

Self-directed learning principles suggest that more experienced peers or mentors can often play a key role in helping evaluate learning outcomes [19]. In the case of our interviewees, who were mostly learning by themselves, it was challenging to find appropriate help when they needed it. Part of the difficulty in obtaining help arose from social challenges (e.g., difficulty finding a community for support).

Nine of our interviewees, mainly from CS backgrounds, confirmed that it was faster for them to learn by asking friends who already had relevant experience or following advice shared on online communities like Facebook groups. However, the majority of our interviewees from non-CS backgrounds expressed challenges in navigating their way through self-learning ML using social means alone. For example, P18, who was trained as a Manufacturing Engineer, attributed the challenges to the interdisciplinary nature of the ML field, which meant that “*there are no ready-made answers*” and that one has to rely on different experts who may be skilled only in “*statistics or [...] good at just teaching the tools or someone who is good at [communicating] the logic of it.*”

Some interviewees, such as P21, added that they felt that “*there's stigma in the professional fields towards people that don't have a CS background that are doing ML.*” Similarly, P03, who had a Mechanical Engineering background but had been practicing Data Analytics for seven years before learning ML added: “*It's hard to be able to convince someone that I can do ML without a formal degree.*” There was a general sense among our interviewees, irrespective of their backgrounds, that connecting with and developing relationships with ML professionals was important for their own progress. However, the

forementioned challenges hindered some of our interviewees from tapping into help sources for individualized feedback.

VIII. DISCUSSION

In this paper, we contribute insights into what motivates informal learners from different backgrounds to pursue ML, how they select their learning strategies, and what types of challenges they face. Our work complements literature in HCI aimed at understanding different populations of informal learners who are acquiring computing-related skills [14, 15, 47, 53]–[55]. By borrowing the lens of self-directed learning [19], we identified the challenges specific to each stage of learning, such as setting objectives, planning a learning path and evaluating outcomes. We found that while informal learners were motivated to make progress, they resorted to trial and error strategies, where they often consulted a resource (e.g., a course) because it was easy to access, without necessarily assessing the benefits of the pursuit (trial). In the absence of such reflections, these pursuits resulted in failure (error) in terms of utilizing time or making progress towards desired outcomes (see Fig. 1 Stage 3). Although researchers have used terms such as ‘informal learning’ and ‘self-directed learning’ interchangeably [5, 56, 57], our findings indicate that self-direction is an advanced metacognitive process that may be challenging to carry out while learning a complex technical skill informally.

A. Importance of understanding the variation in motivations for learning ML informally

First, our study revealed the broad diversity that exists within the population of informal learners of ML (see Table I), complementing earlier studies that have identified specific sets of ML learners [7, 30, 58]. Most of our interviewees were not ML specialists and wanted to learn ML for personal interest tasks (e.g., in sports, finance) or in their professional domain (e.g., in education, health). Similar to the growth of end-user programmers across several domains [59], it is likely that there will be an increase in the population of people from non-CS backgrounds who create and adapt ML-specific solutions. But, as we found in our study, the challenge of learning ML can be more acute because learners have to master not only the programming-level details, but also understand the structure of their data, the nuances of the underlying domain, and advanced mathematical and statistical concepts.

By using the lens of self-direction, we found that most learners found it challenging to accurately diagnose their learning needs and resorted to using familiar strategies. For example, learners with a background in math often resorted to performing derivations of mathematical formulae used in ML algorithms, while those with prior programming knowledge sought code examples which helped them structure their programs. However, not all learners who pursue ML are equipped with effective sense-making tools from relevant prior knowledge. This suggests that learners might benefit from being introduced to a range of effective learning strategies from more experienced learners with a similar background, who

can serve as “mastery” or “coping” models [60]. Learners may also benefit from alternative ways of gauging their progress, as their usual results-focused approach does not factor in the uncertainty of producing a usable model.

Prior studies have identified a need to expand ML literacy by accommodating the needs of people from backgrounds beyond CS [27]. Empowering stakeholders of ML systems with an understanding of the underlying mechanics may even help them become better critics of ML system design and help achieve the vision for responsible AI systems [18, 61]. Our study is only one step in this direction, and further studies are needed from learner-centered perspectives [17] to accommodate the domain-specific needs of informal ML learners.

B. Promoting reflective learning strategies for ML

The informal learners of ML in our study needed to identify several high-value resources to help them develop their mental model of the problem and solution, which quickly became overwhelming given the deluge of ML resources. These learners often proceeded with ill-defined goals and vague success metrics and often struggled in choosing resources and learning strategies that may be helpful for them. What we observed in learners’ behaviors is close to what has been described as “information foraging” [49]. Our interviewees were opportunistic rather than strategic about their information-seeking process. We found that learners’ attention was usually focused on producing immediate results at the cost of developing long term competency, what has previously been termed as the *production bias* [62]. Additionally, our participants’ implementation-oriented approach could be explained by *assimilation bias* [62] as learners tended to adhere to familiar problem-solving techniques.

New tools can support self-direction among informal learners of ML to allow them to optimize their learning time and to become aware of potential biases [63]. One way to discover the factors that favor learning could be by providing learners with means of observing and tracking their experience *across mediums* (e.g., inspired by [64]–[70]). For example, visualization techniques could show learners the patterns from interaction traces [71] on various platforms they use for learning ML. Additionally, personal logs produced in the process of learning (e.g., notes, to-dos, calendars) could augment these self-awareness techniques. Future work could explore how to capture the natural externalizations of learners’ thoughts through different mediums. Such personal data could then be used to create digital forms of bullet journals [72] that the learner could use for self-reflections (Fig. 1 Stage 3).

C. Personalized success metrics for gauging learning progress

The problem of vague goals and personal success metrics described by our interviewees has also appeared in prior work [68, 70]. Providing tools for determining the criteria for success can provide learners with contextual awareness beyond their immediate task needs, and subsequently prompt them to diversify their support systems for learning ML.

Future work could also explore the design of a learning tracking system with optional self-defined metrics that adaptively gauge progress while learning ML. Metrics could include the progress in learning new vocabulary, or measure application of a newly learned concept in a prototype project. An adaptive learning process can lead to the discovery of unforeseen problems and accelerate problem resolution towards learner’s objectives. Continual re-evaluation and iteration of the goals [68] could serve as invaluable feedback of the learning progress (Fig. 1 Stage 3). This could be tailored for ML and other complex technical topics where continuous learning is key. Future work could investigate how reflections could be integrated in the informal learners’ routine, such as through incorporating subtle reminders or reflective activities within the learner’s calendar [73].

D. Limitations and Future Work

Although we recruited interviewees from diverse demographic and professional backgrounds, those who responded to our screener survey are likely more proactive and autodidactic than the general learner population. We used self-report to collect qualitative data from learners’ recollection of their experiences, and therefore the reported information may differ from their real-time struggles while learning. Note that the focus of our conversations was on higher-level learning strategies rather than the lower-level technical details of struggling with a specific programming language or framework. Future studies could use observational or in-situ data collection methods such as Experience Sampling [65, 74] or journaling to collect real-time evidence of struggle. To complement our qualitative work, researchers can use empirical findings from Learning Sciences to design alternatives adapted for use in informal contexts. Lastly, we did not explore demographic differences, for example background-specific, gender-specific, or occupation-specific needs or learning goals, which is another avenue for future work.

IX. CONCLUSION

We have contributed insights from interviews with informal learners of ML, shedding light on their diverse backgrounds, motivations, and learning strategies. Using the metacognitive lens of self-directed learning, we identified challenges across the three stages of self-direction that prevent informal learners from strategically gauging their own progress and reflecting about their learning. Despite being highly motivated and investing a lot of time and effort, many of the informal learners of ML in our study felt overwhelmed and struggled to keep up. There are several opportunities for future research to use learner-centered and human-centered approaches to better understand emerging populations of informal learners and better support these learners with interventions using self-monitoring and self-reflection techniques. Ultimately, there is a need to better support lifelong learning of ML and other complex technical topics among populations who will not necessarily be formally trained in CS or related fields.

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