

Analysis of Motivations in Machine Learning Textbooks

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Abstract

Recent work has explored the interests that draw learners to Machine Learning (ML), aiming to support their success and broaden participation in the field. However, whether strategies used in textbooks align with these interests is unexplored. We perform a thematic analysis of the introductions from ten openly available ML textbooks to identify their motivational strategies and compare them with student interests documented in prior research. We find that textbooks frequently motivate learners in their introductions by setting learning goals, previewing core ML topics to be covered, showcasing applications and current successes, and, less often, by using learner-centered strategies such as reassurance or curiosity prompts. We group these motivations into three overarching themes: theoretical, practical, and learner-centered. These motivations largely align with student interests, particularly in theory and applications, even in textbooks published before the recent surge of ML and Artificial Intelligence. These findings reveal how textbooks frame ML’s value and offer evidence-based guidance for developing future materials that better engage and support diverse learners.

Introduction

Textbooks serve as foundational pedagogical resources across disciplines; as such, there is a history of textbook content analysis across different fields (Halawa, Hsu, and Zhang 2023; Zeynivandnezhad, Saralar-Aras, and Halai 2024; Van Steenbrugge, Valcke, and Desoete 2013). Textbook content influences how its readers process, retain, and critically engage with content; it also influences academic outcomes, personal development, awareness of social issues, and beyond (Apple and Christian-Smith 2017). Educators frequently adapt their instructional approaches based on the textbooks they use (Chiappetta, Fillman, and Sethna 1991; Fan and Kaeley 2000). Within computer science, machine learning (ML) textbooks not only describe technical procedures such as model architectures, but also shape the paradigmatic worldview through which readers first understand the field (Amoore et al. 2023). Thus, the language used and perspectives taken by textbooks impact more than just a student’s technical knowledge gain.

Our goal is to understand how textbooks motivate one to learn ML. We believe this to be an important topic since ML

can be both deeply theoretical and have a range of practical applications, and thus learners’ interests in ML are diverse. Petrescu, Pop, and Dan Mihoc (2023), Mao et al. (2023), and Sibia et al. (2025) report that ML applications and the “hype” surrounding Artificial Intelligence (AI) are strong motivations for learners. However, it is not clear to what extent textbook resources introduce ML content in ways that align with these interests.

This study thus asks the following research questions:

- RQ1. How are motivational strategies commonly used when introducing ML in textbooks?
- RQ2. How do these motivational strategies align with student interests in the theory and applications of ML, as identified in prior research?

Despite the influence of textbooks, few studies have examined how they introduce, structure, and communicate ML. We thus analyze the introduction chapters of ten openly-available textbooks, and study the strategies used to motivate readers to learn ML. We emphasize the balance between theory, application, and the experience of the learners.

Related Work

Textbook Analysis

Textbook analysis is a method in education research for examining the structure, content, language, visual design, and pedagogical strategies in textbooks (Pingel 2010). Methods used in textbook analysis include quantitative (Wilkinson 1999) and qualitative content analysis (Zeynivandnezhad, Saralar-Aras, and Halai 2024), and framework development approaches—for example, Halawa, Hsu, and Zhang (2023) integrated motivational analysis into a five-part framework for textbook evaluation.

In computing education, several studies have analyzed textbooks to improve curriculum design or identify pedagogical trends: Means (1988) tracked content evolution in ten introductory programming textbooks, while Kawamata et al. (2021) applied Latent Dirichlet Allocation (LDA) and clustering to examine topic progression in sixteen CS textbooks. McMaster et al. (2017) converted twenty introductory Java and Python textbooks into corpora and found consistent approaches to basic programming concepts. In AI education, Maxwell (1998) analyzed six undergraduate computer vision textbooks and highlighted the need for more

accessible, up-to-date content. Investigations specifically focused on CS subfields such as machine learning remain otherwise scarce. By comparison, other STEM disciplines such as mathematics (Sunday 2014; Zeynivandnezhad, Saralar-Aras, and Halai 2024; Son and Diletti 2017; Rivers 1990; Johansson 2003), statistics (Cobb 1987; Setiawan 2020; Han et al. 2011; Dunn et al. 2017), and physics (Wilkinson 1999) have a longer and more established history of textbook analysis.

Motivation Theories

Motivation is central to how students engage with and retain content, and prior research shows a strong link between self-directed learning, academic achievement, and motivation (Yurdal and Toraman 2023). Well-designed textbooks should be pedagogically sound and engaging, using motivational strategies to help students stay engaged and self-regulate without instructor or peer support (Keller 1987). We describe several frameworks for understanding how and why students engage with learning tasks.

Self-Determination Theory (SDT) SDT posits that motivation is driven by the satisfaction of three basic psychological needs: autonomy (experiencing a sense of volition or choice), competence (feeling effective and capable), and relatedness (feeling connected to others) (Deci and Ryan 1985). When these needs are met, individuals are more likely to experience intrinsic motivation and well-being. SDT has been used in textbook analysis to understand students' textbook choice and usage (Derryberry and Wininger 2008).

Expectancy-Value Theory (EVT) EVT states that motivation depends on expectancy (the belief in likelihood of success) and value (the perceived importance, usefulness, or interest of the task) (Wigfield 1994). It also incorporates 'cost,' which includes perceived effort, anxiety, or lost opportunities associated with the task. In textbooks, EVT supports the argument that clear goals support students' confidence in success, and real-world applications enhance perceived value (Halawa, Hsu, and Zhang 2023).

ARCS Model of Motivation ARCS identifies four components for sustaining motivation: Attention (capturing interest), Relevance (aligning content with needs and goals), Confidence (belief in the ability to succeed), and Satisfaction (positive outcomes from engagement) (Keller 1987).

L2 Motivational Self System (L2MSS) Introduced by Dörnyei et al. (2009) in the context of second language (L2) learning, this theory comprises the Ideal Self (aspirations), the Ought-to Self (external expectations), and the Learning Experience (attitudes toward tasks). In textbook analysis, this theory highlights language that supports aspirational identity, external pressures, or reflections on prior learning (Bergman and Svensson 2022).

Mindset Theory This theory distinguishes between a fixed mindset and a growth mindset, shaping how students approach challenges, setbacks, and effort (Dweck and Leggett 1988). A fixed mindset assumes that abilities are innate and unchangeable, while a growth mindset holds that

abilities can be developed through effort and learning. In textbooks, this theory can be applied to identify whether materials normalize struggle and fostering a growth mindset in learners.

Academic Motivation Scale (AMS) AMS classifies motivation into intrinsic (to know, to accomplish, to experience stimulation), extrinsic (external regulation, introjected regulation, identified regulation), and amotivation (lack of intent) (Vallerand et al. 1992). AMS has been adapted in educational studies to assess motivational types in instructional design and materials (Derryberry and Wininger 2008).

Goal-Setting Theory Motivation is enhanced by specific, challenging goals, which direct attention, mobilize effort, increase persistence, and promote strategic planning (Locke and Latham 2015). Clear and attainable goals are more effective than vague or easy ones. Prior work on textbook analysis highlights that goal statements can help students structure their learning and monitor progress (Halawa, Hsu, and Zhang 2023).

Machine Learning Motivation

Prior work has studied both students' perceptions of AI/ML and their interest in it. Studies show that majors in CS or Engineering (Sulmont, Patitsas, and Cooperstock 2019) and non-majors (Gray et al. 2022) view learning ML/AI as important. Many students believe that ML/AI will influence their future careers, even in jobs beyond the computing field (Barretto et al. 2021). Some perceive ML/AI as intimidating and inaccessible (Barretto et al. 2021), often due to the CS or math requirements (Sulmont, Patitsas, and Cooperstock 2019). Bewersdorff et al. (2023) provided a broader literature review on the perceptions of AI.

Sibia et al. (2025) outlined three main reasons why students are interested in ML: an interest in the *application* of ML, a wish to *explore* an unfamiliar area, and a desire to build a *strong theoretical foundation*. These motivations are also reported elsewhere (Petrescu, Pop, and Dan Mihoc 2023). Differences in ML interest by demographics have also been reported. Kovačević and Demić (2024) found that men self-reported greater interest than women. Petrescu, Pop, and Dan Mihoc (2023) found that although women are more interested in ML, men are more likely to desire a higher level of understanding of AI. In Barretto et al. (2021), students from underrepresented groups are more interested in the societal impacts of ML/AI. Using the same data as Sibia et al. (2025), Richardson et al. (2025) found that women were more interested than men in the applications of ML at the beginning of an ML course, and those without ML background tended to be more interested in such a course due to its "hype", though none of the effects were statistically significant.

Method

A Google internet search of the query "Introductory ML textbooks" was conducted to identify introductory ML textbooks. We only included books that are freely accessible online and include content on regression to ensure sufficient

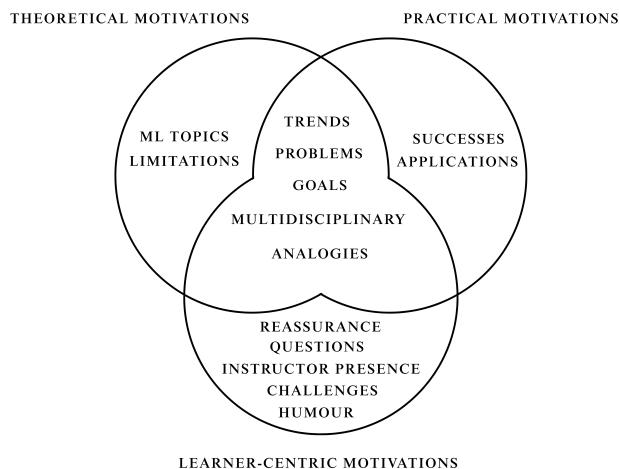


Figure 1. Summary of Motivations in 10 ML/AI Textbooks

coverage for beginners. After a review by an ML educator, we assembled a final list of 10 textbooks, shown in Table 1. In this table, the textbooks are anonymized: each textbook is assigned a numerical identifier (T1-T10), and direct quotes are paraphrased where necessary to prevent identification. We focused our analysis on the introduction chapter of each textbook because these sections serve critical pedagogical functions, including gaining learner attention and informing learners of objectives (Gagné and Briggs 1988).

Thematic analysis of the introductions was carried out by two researchers: an ML educator and a research assistant with CS education research experience. We used a hybrid coding approach (Fereday and Muir-Cochrane 2006), which allowed us to uncover emerging motivational strategies unique to ML textbooks while also identifying strategies consistent with themes from prior work analyzing STEM textbooks.

The researchers each independently coded the introductions from two ML textbooks. The researchers then held several discussions to resolve discrepancies and refine code definitions. Discrepancies often arose in boundary cases (e.g., distinguishing between *Current Successes* and *Applications*), which were resolved through these discussions. The codebook was refined accordingly. This iterative process continued until a stable set of 14 motivational codes was finalized, which were then applied to the remaining eight textbooks. Any new codes that arose in later books were discussed and ultimately merged with existing ones to maintain consistency. Of the 14 codes, 8 inductive codes were developed through the initial open coding. The remaining 6 deductive codes were drawn from literature on motivation and textbook analysis in STEM:

- Analogies (Zeynivandnezhad, Saralar-Aras, and Halai 2024; Huang et al. 2022)
- Humour (Zeynivandnezhad, Saralar-Aras, and Halai 2024)

- Curiosity Prompts (Zeynivandnezhad, Saralar-Aras, and Halai 2024)
- Reassurance (Deci and Ryan 1985; Dweck and Leggett 1988),
- Challenge Invitation (Zeynivandnezhad, Saralar-Aras, and Halai 2024; Huang et al. 2022), and
- Instructor Presence (Zeynivandnezhad, Saralar-Aras, and Halai 2024).

These codes, along with their descriptions and supporting motivation theories, are shown in Table 2.

After finalizing the codebook, we coded segments in each textbook’s introduction section, and recorded where motivational language was used. A “coded instance” refers to one application of a code to a segment, regardless of the length of the segment. A single segment could receive multiple codes. We counted the number of times each code appeared per book. To account for differences in introduction length, raw counts were normalized by dividing coded instances by chapter word count and scaling to frequencies per 1,000 words. This is shown in Table 3.

Results

We begin by analyzing how often each code appeared across the ten ML textbook introductions. Table 3 shows which motivational approaches are most common and which are less emphasized, normalized to the length of the introduction section. These patterns are interpreted through motivational theories, shown in Table 2, and grouped into four themes—theoretical, practical, learner-centered, and mixed—to illustrate how textbooks engage readers (Figure 1). Broadly, theoretical motivations supported conceptual competence, practical motivations emphasized real-world applications, learner-centered strategies fostered confidence and autonomy, and mixed strategies spanned multiple categories.

Theoretical Motivation

Theoretical motivations include those that engage students’ interests in conceptual foundations, principles, and the intellectual challenges of the field. In ML textbook introductions, theoretical motivation often appears through the presentation of key ML topics and the discussion of specific limitations of models.

ML Topics All textbooks introduced foundational ML concepts such as classification, regression, probability theory, loss functions, etc., frequently paired with signposting phrases (e.g., “In this chapter, we will...” or “Chapter 2 focuses on...”). In some, such as T2 and T8, signposting and topic previews were used very frequently to frame a clear learning journey. Others, like T5, briefly mentioned concepts and deferred deeper explanation to later chapters. Some, like T6, took a more formal approach, framing ML techniques as precise mathematical problems from the outset (e.g., clustering was introduced as “the problem of partitioning items into homogeneous sets”). The textbooks also highlighted the distinctions between these problems, often emphasizing their mathematical structure.

Textbook	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Year	1997	2001	2008	2014	2016	2018	2023	2024	2025	2025

Table 1. Textbooks and their publication years.

Codes	Description	Supporting Motivational Theories
Learning Goals	Statements describing what readers will learn.	SDT, ARCS
Limitations	Acknowledges limitations of specific ML methods, tools, or platforms.	SDT, EVT, Goal-Setting Theory
ML Topics	Mathematical or conceptual frameworks such as loss functions, or learning theory.	EVT, ARCS
Applications	Cases of how ML is being applied in the real-world.	SDT, EVT, ARCS, L2MSS
Current Successes	Mentions of specific real-world successes of ML methods or concepts.	EVT, L2MSS
Field-Wide Problems	Broader ML issues that transcend any single system.	EVT, AMS
Future Trends	Poses future ideas, encourages the reader to imagine where ML might go.	ARCS, L2MSS
Multidisciplinary Overlap	Shows ML's interaction with other disciplines.	SDT, ARCS, AMS
Analogies	Analogies or toy examples (e.g., cooking, sports) used to aid understanding.	SDT, ARCS
Humour	Use of jokes, memes, or light-hearted commentary to connect with learners.	ARCS
Curiosity Prompts	Questions or curiosity-driven prompts that invite critical thinking.	ARCS, AMS
Reassurance	Phrases that validate student struggles or encourage continued effort.	SDT, Mindset Theory
Challenge Invitations	Phrasing that invites learners to learn, even if it is difficult.	SDT, Mindset Theory, Goal-Setting Theory
Instructor Presence	Narrative cues that make the author feel present in the text.	SDT, ARCS

Table 2. Codebook of textbook motivations and corresponding motivational theories supporting them

Limitations Although less frequent, *Limitations* appeared in textbooks like T5 and T10. By highlighting constraints, these introductions encouraged critical thinking and positioned ML as a dynamic, evolving field. These instances often critiqued older or constrained ML models (e.g., T5 highlighted the challenges of the knowledge-base approach, noting that projects like Cyc (Lenat and Guha 1989) struggled to capture real-world complexity), providing learners with reasons and motivations to learn new tools discussed in the textbook. The textbooks that discussed limitations were all written after 2016, which may reflect increased awareness of ML's boundaries in contemporary discourse.

Practical Motivations

ML can be applied to many disciplines, and this practical aspect of ML is leveraged in textbook introductions in distinct ways. Some discussions of applications cover broad domains. Other discussions are about specific successes, outlining concrete achievements where ML demonstrated notable results.

Applications Most textbooks outlined broad areas of ML applications, using these areas as motivations for studying ML. In particular, T1, T3, T5, and T9 devote comparable and significant space to these applications. Common examples included image recognition and speech processing, often presented early to spark engagement. Many descriptions were general or hypothetical, such as the statement of T4

that “Deep learning has been useful in many software disciplines such as computer vision, speech and audio processing, NLP, etc.”

Current Successes Several textbooks described specific and notable ML achievements, such as TD-Gammon, SPHINX, IBM's Deep Blue, spam filtering with Naive Bayes, and logistic regression for medical prediction. This was the second-most frequent code overall, with particularly high usage in T1 and T2.

Learner-Centric Motivations

As shown in Table 3, Learner-centered strategies were generally underrepresented in introductions of ML textbooks. For instance, *Reassurance*, *Humour*, and *Challenge Invitations* were rare across most books. Additionally, T8 showed the highest *Instructor Presence*, suggesting that this book aimed to establish a more conversational and empathetic tone. Likewise, some textbooks, such as T7 and T10, utilized numerous learner-centric motivations.

Reassurance Only three textbooks, all published in the last few years, included phrases that validated difficulty and encouraged persistence (e.g., “do not worry if this seems confusing”), suggesting it may be a more recent stylistic development in ML education. T8 employed this most, pairing it with an emphasis on *ML topics*. For example, the book explains that “A challenge we face in ML is that concepts and

Codes	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10
Learning Goals	3.3	2.1	1.6	1.2	2.3	0.7	0.3	4.7	0.7	0.7
Limitations	-	-	-	-	0.8	-	0.1	-	-	0.8
ML Topics	6.6	10.0	4.7	3.0	5.0	9.3	1.9	6.7	2.9	1.2
Applications	3.3	-	3.1	2.1	3.1	2.9	0.4	-	3.1	0.7
Current Successes	6.7	6.4	2.8	0.6	1.5	2.1	2.0	1.3	3.6	1.2
Field-Wide Problems	1.3	1.4	0.9	0.3	4.6	-	0.5	0.7	0.5	1.2
Future Trends	4.7	-	0.3	0.3	-	-	0.2	-	0.5	0.3
Multidisciplinary Overlap	1.3	-	-	0.3	-	0.4	-	-	1.4	2.2
Analogies	-	-	2.8	1.5	1.5	-	0.7	-	0.7	0.5
Humour	-	0.7	-	-	-	-	0.1	-	-	-
Curiosity Prompts	-	0.7	0.3	0.9	-	1.8	1.0	-	0.5	0.5
Reassurance	-	-	-	-	-	-	0.2	0.7	-	0.2
Challenge Invitations	-	0.7	-	0.3	-	-	0.4	0.7	0.2	0.2
Instructor Presence	1.3	0.7	0.9	-	-	-	0.6	2.0	-	0.2

Table 3. Descriptive statistics for the distribution of motivation codes in textbook introductions (normalized per 1,000 words)

words are slippery”, before explaining the terms and concepts. This framing acknowledges that a learner’s confusion is normal, and may reduce intimidation and feelings of non-belonging.

Curiosity Prompts Found in seven textbooks, these included rhetorical questions and open-ended provocations designed to spark interest or critical reflection. Examples of these kinds of prompts included “what if AI could transcend its current capabilities?” [T9] and “this is just a glimpse of the ideas behind a decade of breakthroughs—much more awaits” [T7].

Challenge Invitation Present in six textbooks, *Challenge Invitations* encouraged readers to take direct action—often through independent activity tasks—before continuing. Authors often challenge students to try coding tasks on their own, such as building a simple speech-based trigger system without external tools or guidance [T7].

Instructor Presence Seen in six books, this code captures instances where the textbook voice feels conversational due to its use of pronouns. Such pronoun use and conversational style were observed most notably in T1 and T8. Example conversational cues include “you might be wondering...” [T1] and “I found that another way to think about this problem is...” [T3].

Humour This motivator was rare, found only in T2 and T7, and appeared as light informal comments or playful asides. For example, T7 playfully opens with a reference to the authors’ need for caffeine. In another instance, T2 uses caricatures to label complex materials.

Mixed Motivations

Some of the motivation codes do not fit neatly into one of the above categories. Instead, these motivations encompass multiple themes.

Learning Goals Common across all textbooks, *Learning Goals* clearly stated desired outcomes (e.g., “in this book, we will teach you ..., a powerful set of techniques driving innovations in areas as diverse as ...” [T7]). Unlike *ML Topics*, which explained what would be covered, *Learning Goals* conveyed why the material mattered and what competence it would build.

Field-Wide Problems Broad ML challenges—such as bias, generalization, and reproducibility—were discussed in several books, with T5 emphasizing them most. For instance, T5 highlighted the long-standing challenge of translating informal, tacit human knowledge, often difficult for people themselves to articulate, into forms that computers could process. This problem exemplifies a field-wide difficulty, since it reflected the broader struggle that went beyond a single algorithm or method. Unlike *Limitations*, which focused on specific models, *Field-Wide Problems* encouraged learners to engage with discipline-wide issues and their societal implications.

Future Trends This code refers to the discussion of where ML is headed, e.g., future applications in domains like healthcare and ethics. Discussions about the possible future of ML were most notable in T1, the oldest book in the set, which in one instance invited readers to imagine when computers could learn from medical records to devise treatments for new diseases.

Multidisciplinary Overlap Several textbooks connected ML to other disciplines, including cognitive science [T1, T9], social sciences [T10], business [T10], and statistics and mathematics [T1, T4, T9, T10]. T10 featured this content most prominently. *Multidisciplinary Overlap* was different from *Application* in that it refers to cases where ML itself incorporates theories, methods, or data from other fields, rather than simply being applied in them.

Analogy The use of analogies and everyday comparisons was prominent in ML textbook introductions we analyzed, with T3 using them the most. For instance, T4 used an analogy connecting supervised learning to a student–teacher relationship. We also included toy examples in this category, used to illustrate specific concepts: for instance, using apples vs. oranges as an example for binary classification [T3]. Analogies and toy examples both aided in making abstract concepts more concrete and relatable.

Discussion

Our study shows that theoretical and practical strategies dominate, while learner-centered strategies are comparatively rare in ML textbook introductions.

RQ1: Motivations in ML Textbooks

Theoretical Motivations Introducing *ML topics* at the outset explicitly signals the value of reading this textbook. This aligns with EVT (Wigfield 1994), which posits that learners engage more when they believe material is valuable. Clear signposting supports learners’ metacognitive skills, such as planning and self-monitoring, by helping them follow the structure of the material and see how individual concepts fit into the broader whole (Mayer 2002; Robinson et al. 2006). Framing concepts as formal problems, as in T6, may further support learners’ belief that the material is meaningful and worth the effort, a key factor in sustaining motivation according to the ARCS theory from Keller (1987). We believe this motivation to be particularly appropriate for learners who have some prior knowledge in ML, and who are self-directed. Although listing the ML Topics does not necessarily motivate readers to learn ML, it explicitly signals the value of reading *this textbook*, for readers who are already seeking this knowledge.

Discussions of *Limitations* encourage learners to value deep understanding and long-term thinking, resonating with Goal-Setting Theory (Locke and Latham 2015) and EVT’s value component (Wigfield 1994). For example, when textbooks highlight limitations, they signal to students that ML is not all-powerful but an evolving field where recognizing boundaries is part of becoming truly competent. According to SDT (Deci and Ryan 1985), understanding limitations can also increase the learners’ sense of competence by preparing students to navigate complex challenges.

Practical Motivations Providing learners with an understanding of how ML can be applied is a common way for textbooks to foster motivation. This is supported by EVT, as real-world applications increase utility value, motivating learners when they perceive knowledge as useful (Wigfield 1994). Evidence of ML’s practical successes further improves students’ expectancy (in EVT), which could strengthen students’ belief that their own efforts can lead to tangible outcomes. From an SDT perspective (Deci and Ryan 1985), these examples can enhance autonomy and relevance by showing how ML connects to societal goals. Similarly, the ARCS model (Keller 1987) emphasizes that real-world relevance captures attention and sustains motivation. The L2 Motivational Self System (Dörnyei et al. 2009) also

supports the idea that highlighting application and societal impact can enable learners to imagine themselves applying ML in personally meaningful contexts.

Learner-Centric Motivations *Reassurance* aligns with mindset theory, which emphasizes that normalizing struggle fosters perseverance (Dweck and Leggett 1988). In parallel, SDT highlights the importance of supporting learner competence and intrinsic motivation by reducing anxiety and fear of failure (Deci and Ryan 1985). These types of motivations are particularly relevant given that students often perceive ML as intimidating and inaccessible (Barretto et al. 2021).

Curiosity Prompts and *Challenge Invitations* both encourage active engagement and self-directed exploration. The former sparks intrinsic motivation and sustained attention by posing open-ended questions (ARCS: attention, relevance (Keller 1987); AMS: intrinsic regulation (Vallerand et al. 1992)), while the latter promotes both learner independence and goal-oriented persistence (Locke and Latham 2015) and also supports identified regulation in SDT by framing challenges as meaningful.

Instructor Presence fosters relatedness in SDT (Deci and Ryan 1985) through simulating dialogue between author and learner and similarly strengthens attention and relevance from the ARCS (Keller 1987) model. Again, given the perceptions of ML/AI as intimidating (Barretto et al. 2021), it is possible for this approach to create a sense that a knowledgeable and supportive figure is guiding the learners.

Finally, *Humour* maps to the ARCS model, particularly the attention and satisfaction components (Keller 1987) by making content more engaging and emotionally positive.

Mixed Motivations Many textbooks present goals that combine theoretical understanding with practical application, speaking directly to diverse learners in order to maintain engagement. *Learning Goals* give learners a clear direction that offers more guidance than *ML Topics*. This combination of scope, purpose, and direction can be especially effective for novice learners who are not as self-regulating, or for learners with less prior ML experience.

Field-Wide Problems align with EVT’s expectancy and value components (Wigfield 1994) by showing learners that they can contribute to important, real-world issues. This increases attainment value, utility value, and intrinsic value (Wigfield 1994; Vallerand et al. 1992).

Future Trends link current learning to anticipated developments in the field. While these descriptions primarily outline the possible future of ML as a discipline, they may also encourage learners to imagine their own place within that evolving landscape, loosely connecting to the “possible selves” framework (Dörnyei et al. 2009). In doing so, they highlight both ML’s practical utility and its theoretical depth.

Multidisciplinary Overlap makes content personally relevant by connecting ML to students’ existing interests or identities. It sustains attention in ARCS (Keller 1987) by introducing novel or unexpected links to other fields; for example, showing creative uses of ML might engage a student interested in the arts. This code also supports autonomy and relatedness in SDT and identified regulation in AMS because students engage with material they find meaning-

ful, not just when they are told. This autonomy can improve persistence and learning outcomes (Deci and Ryan 1985; Vallerand et al. 1992).

Analogies—including everyday comparisons and concept-focused examples—help reduce cognitive load, making complex ideas easier to understand. Through this, they align with SDT’s autonomy and relevance components and ARCS’s attention and satisfaction principles (Deci and Ryan 1985; Keller 1987).

RQ2: Comparisons with Student Interest

The emphasis on practical application in textbooks aligns with the motivations reported by students (Sibia et al. 2025; Petrescu, Pop, and Dan Mihoc 2023; Mao et al. 2023). The codes *Applications*, *Current Successes*, *Multidisciplinary Overlap*, and *Field-Wide Problems* highlight the use of ML within and beyond CS, showing learners how their knowledge could be widely applied. In addition to applications and current successes, students value other practical aspects, such as employability (Sibia et al. 2025; Mao et al. 2023).

Learning the theory (and mathematics) of ML is not the most common motivators for students reported in prior work (Sibia et al. 2025). Still, textbooks are great tools for highly self-directed students to explore a field in a way that supports autonomy. Thus, we frame clear descriptions of *ML Topics* and *Limitations* as motivations. Both *Field-Wide Problems* and *Limitations* can motivate students by showing what is possible in ML and what is not. Additionally, motivations related to theory spark students’ curiosity about how and why ML methods work, fostering long-term engagement (Sibia et al. 2025; Petrescu, Pop, and Dan Mihoc 2023).

In terms of learner-centric motivations, prior work shows that students are curious about ML despite limited exposure. Sibia et al. (2025) and Mao et al. (2023) find that some students are drawn to ML due to its rapid growth and “hype”, corresponding to the theme *Future Trends*. These students tend to have less prior knowledge in ML (Richardson et al. 2025), and may require support. Identity, self-efficacy, and motivation are also important aspects to consider for broadening participation. (Isomöttönen, Lakanen, and Valkonen 2025) Thus, while learner-centric prompts are rare, we believe them to be important artifacts for study. For example, some textbook authors use *Curiosity Prompts* in an attempt to motivate novice learners to explore ML. Mentorship is another learner motivation that is valued by students (Mao et al. 2023); reader reactions to *Instructor Presence* and *Reassurance* in textbooks could be a topic for further research.

Sibia et al. (2025) found that some students are challenged by conceptual aspects of ML. *Analogies*, which can relate to both the theoretical and practical aspects of ML, leverage learners’ prior knowledge and experience. Analogies link abstract ideas to concrete, real-life examples more familiar to readers. Along with *Curiosity Prompts*, *Analogies* also engage the affective side of learning, stimulating interest and supporting deeper motivation (Pekrun 2006).

We observe that newer textbooks tend to adopt a more learner-centric and inclusive orientation. This may reflect broader pedagogical shifts toward inclusivity and student engagement in CS education (Letaw et al. 2022; Cao et al.

2023; Lin 2022; Tripathi and Thakkar 2025). At the same time, there is a form of survival bias in our corpus: highly technical textbooks, which often prioritize dense theoretical content over explicit learner support, may persist and remain widely circulated as authoritative references.

Limitations and Future Work

This study provides a qualitative analysis of motivational strategies in ML textbook introductions, but several limitations shape its scope. Like all qualitative studies, researcher bias is possible, although we attempted to mitigate this by having coders with differing perspectives (student and ML educator).

As we focused on the introduction section of ten openly available textbooks, we acknowledge that our findings do not reflect all chapters of an ML textbook, or ML textbooks in general. Moreover, while we analyzed openly available textbooks, we excluded proprietary or widely used commercial texts, which may differ in style. Expanding to a larger and diverse textbook database would improve generalizability. We also only analyzed textbooks, rather than the growing set of online courses, videos, and interactive tutorials available for novice learners of ML. Motivational approaches for these resources could differ.

As this study used a content analysis methodology, we do not know how textbook readers react to the motivational strategies used; we do not know whether the strategies used are effective. We leveraged prior work on ML interests of university students for comparison, but acknowledge that these interests could differ from textbook readers. We also acknowledge that prior work on student interest in ML is typically comprised of single institution studies with narrow scope. Motivations could differ by geographic location, study areas, and student characteristics.

Conclusion

This study reveals how ML textbook introductions motivate learners through theoretical, practical, and learner-centered strategies. Many of these strategies align well with prior work on student interests in ML. However, while theoretical rigor and real-world relevance are well represented in motivations in ML textbooks, more personal and inclusive approaches remain scarce, especially in older texts. The limited presence of learner-centered motivators aligns with documented perceptions of ML as intimidating, particularly among students who doubt their mathematical preparation. Although we did not conduct interview studies to see how learner-centered motivations affect readers, future research could explore whether these textbook patterns contribute to shaping how students perceive the field and their place within it.

Our findings invite textbook authors, educators, and curriculum designers to think beyond content delivery and to design with intention, empathy, and inclusivity in mind. The many motivation theories tell us that motivation strategies matter; textbook introductions (and other resources) can be an enabler of who chooses to learn ML and who feel that they belong.

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