

Visual-AM: A Visual No-Code Web Tool to Support the Study of Machine Learning

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Abstract. *This research presents Visual-AM, a no-code visual web tool developed using the Design Science Research Methodology to support the study of machine learning. The tool enables the practical exploration of models, regardless of the user's coding experience. Its evaluation was conducted with volunteer undergraduate students from the Bioprocess Engineering program at Federal University of Itajubá, using mixed-methods questionnaires that examined the respondents' profiles and their experiences and perceptions of the use of the tool. The results indicated a predominance of positive evaluations, suggesting good acceptance and potential as a didactic support resource for machine learning, particularly for the constructs "Ease of Use", "Information Flow", "Engagement", "Sense of Progress", and "Contribution of Visual Resources".*

Resumo. *Esta pesquisa apresenta a Visual-AM, uma ferramenta web visual e no-code desenvolvida com base na Design Science Research Methodology para apoiar o estudo de aprendizado de máquina (AM). A ferramenta permite a exploração prática de modelos, independentemente do nível de experiência do usuário em programação. Sua avaliação foi realizada com graduandos voluntários do curso de Engenharia de Bioprocessos da Universidade Federal de Itajubá, por meio de questionários mistos que investigaram o perfil dos respondentes e suas experiências e percepções sobre o uso da ferramenta. Os resultados indicaram predominância de avaliações positivas, sugerindo boa aceitação e potencial como recurso de apoio didático ao estudo de AM, considerando os construtos "Facilidade de Uso", "Fluidez Informacional", "Engajamento", "Sensação de Progresso" e "Contribuição dos Recursos Visuais".*

1. Introduction

Machine learning (ML) technology is present in devices and services that are increasingly becoming part of people's lives [Mohseni *et al.* 2019]. Its growing influence on society highlights the importance of educating individuals so that they become capable not only of understanding how products and services based on this technology work, but also of proposing new solutions and of participating in discussions about policies and regulations related to this context [Sulmont *et al.* 2019; Lao 2020]. However, despite the importance of this technology, its use involves significant challenges [Abd Rahman *et al.* 2021], since building ML models requires mastering complex concepts and performing multiple steps, such as data acquisition, algorithm selection, and performance evaluation, which can

make the process intimidating for new users [Raff *et al.* 2019; Gresse von Wangenheim *et al.* 2021]. A lack of understanding of the fundamental principles of ML can lead to a steep learning curve, especially for non-computer scientists, since grasping the principles behind ML algorithms requires proficiency in programming, data analysis tools, and mathematics and statistics [Deisenroth *et al.* 2020; Askitas 2024]. Additionally, factors such as the difficulty in interpreting the decisions made by some models and the complexity of selecting algorithms and hyperparameters make the learning process even more challenging for beginners [Carvalho *et al.* 2019; Wu *et al.* 2019]. This situation suggests that ML could become more widely used if its concepts were easier to understand, making initiatives that promote simplified approaches to enable more direct interactions with the models desirable [Thin-Yin and Jonathan 2020]. In this regard, approaches based on visual programming languages have proven to be more accessible alternatives for non-programmers [Korus *et al.* 2021]. These approaches rely on graphical user interfaces, which serve as the interface between the user and the system, typically featuring elements such as buttons, checkboxes, and sliders [Burnett 1999; Podrzaj 2019; Jiang *et al.* 2024].

Regarding democratizing access to tools, web-based applications have stood out for eliminating the need for downloads and installations, allowing access across different devices and operating systems [Wang and Durrant 2022; Goh *et al.* 2023]. Part of this is due to cloud computing, which serves as a strategic enabler, allowing software applications to be processed by remote servers, thereby mitigating barriers posed by the user's local hardware [Sultan 2013; Malta 2025]. A growing body of research has focused on creating interfaces that facilitate the understanding, analysis, and sharing of insights into ML systems [Bäuerle *et al.* 2022], such as the web application proposed by Ferdous *et al.* (2023) for chemists and biologists to apply predictive models in their drug discovery research without requiring programming proficiency. However, in addition to tools focused on the practical application of models, it is important to analyze the landscape of web platforms specifically designed to facilitate the study of ML fundamentals. Aiming to make this field of knowledge more accessible, this paper presents Visual-AM, a no-code visual web tool that supports ML study in higher education through interactive resources. The solution integrates theory and practice through progressive modules with interactive activities and immediate feedback, fostering active learning and reducing cognitive barriers, which is its main contribution. After its development, the tool was evaluated by a group of volunteer undergraduate students, who completed questionnaires to identify user profiles and analyze their experiences and perceptions of its use. Evaluation results indicate high levels of user acceptance, usability, and perceived learning, highlighting the tool's potential as an educational resource. Additionally, the study advances the state of the art in web-based interactive tools for ML education in higher education. Finally, the use of Design Science Research Methodology (DSRM) [Peppers *et al.* 2007; Freitas Junior *et al.* 2017] provides a structured, replicable methodological model for developing and evaluating of educational artifacts, another contribution of this research.

In addition to the introduction, Section 2 presents the related works; Section 3 details the tool developed and the research methodology used; Section 4 discusses the results; and finally, Section 5 outlines the conclusions and opportunities for future work.

2. Related Works

The state-of-the-art review of web-based visual tools designed for teaching ML in higher education was based on the systematic mapping study conducted by da Silva *et al.* (2024),

through which eight publications were identified; their artifacts consisted of free web-based tools for studying ML [Harley 2015; Smilkov *et al.* 2017; Kahng *et al.* 2018; Carney *et al.* 2020; Estevez *et al.* 2019; Kahn *et al.* 2020; Schultze *et al.* 2020; Wang *et al.* 2020]. Note that platforms from major technology providers (such as *Google Cloud*, *AWS*, *Microsoft Learn*, and *Huawei Cloud Academy*) were not considered in this study because they are geared toward broad-spectrum technical training [Abell *et al.* 2021; Meyer Jr. and Billionniere 2021; Sang *et al.* 2023], thus falling outside the scope of visual tools focused on teaching the fundamentals of ML. The results of this systematic mapping study revealed a predominance of tools focused on neural networks and image classification tasks, with a majority of *JavaScript*-based graphical interfaces and buttons as the most used interactive elements to simplify interactions with the models. Most of the publications analyzed were observed to lack methodologically detailed evaluations of their respective artifacts. Given the limited number of web-based visual tools for studying ML identified in this systematic mapping study, few projects aim to facilitate research in this area, underscoring the importance of new initiatives.

Unlike approaches focused on isolated activities – such as tools that address only neural networks for classification – this work integrates, within a single interactive, no-code web environment, multiple activities spanning the stages of processing for supervised and unsupervised learning models. Thus, we propose developing an intuitive tool that enables users to explore ML techniques and algorithms, thereby supporting the training of college students in the fundamentals of this emerging field.

3. Method

3.1 Visual-AM Tool

Visual-AM is a no-code, visual web tool with interactive features, designed to enable students to conduct ML studies outside the classroom, in line with their preferences. Developed in *Python*, the tool uses the *Streamlit* framework, which makes it responsive and accessible across various devices, including computers and smartphones. Additionally, its hosting on the *Streamlit Community Cloud* ensures that model processing occurs remotely, making it accessible even on devices with limited hardware. Its interface was designed and developed to facilitate a seamless transition between theory and practice, making it easier for college students to get started with ML. The tool can be accessed via the following link: <https://visual-am.streamlit.app/>.

This research was conducted based on the DSRM [Peffer *et al.* 2007; Freitas Junior *et al.* 2017], consisting of the following steps: (i) investigation of the state of the art regarding the use of visual tools for the study of ML; (ii) definition of the areas within the field of ML to be strategically addressed to meet the research objectives; (iii) development of an artifact – a visual and interactive computational tool for studying ML – aligned with pedagogical procedures that support overcoming challenges commonly faced by students and faculty; (iv) collaboration with undergraduate students to conduct functional tests; (v) evaluation of the proposed artifact contribution to the study of ML from the student's perspective; (vi) making the tool available and publishing this study.

To accommodate the gradual increase in study complexity, the tool content has been divided into distinct topics. The aim is to introduce users to key concepts in the context of ML before they tackle its practical content. Table 1 presents summaries of the topics covered by Visual-AM. The practical activity topics in Visual-AM use different datasets to contextualize the case studies, including classic datasets from the literature such as “*Iris*” [Fisher 1936], “*Wine*” [Aeberhard and Forina 1991], and “*Seeds*”

[Charytanowicz *et al.* 2012]. In addition, datasets such as “*Mall Customers*” [Kaggle 2017] and datasets that have undergone educational adaptations are used: the “*Pima Indians Diabetes*” dataset [UCI Machine Learning Repository 2016] was used in a version previously balanced by the authors, while the “*Banknote Authentication*” [Lohweg 2013] underwent feature scaling, balancing, and translation processes, resulting in the “*Autenticação de cédulas*” dataset. Finally, the tool also uses synthetic datasets created by the authors, including “*Uvas Phomtson*,” “*Aluguéis Ijabutá*,” “*Frutas*,” and “*Animais*,” which are made available in a dedicated repository: https://github.com/da-silva-d-w/Datasets_da_Visual-AM.

Table 1. Summary of topics available in the Visual-AM tool. Source: The authors.

Topic	Description
Home	This section introduces the tool, its purpose, visual features, and instructions for customizing the interface.
Introduction: Basic concepts	This section introduces concepts of ML, artificial intelligence, and deep learning, as well as supervised and unsupervised learning.
Next steps: Let's get to work	This section explains how the introductory concepts are applied to practical topics, mentioning guided progression and the impact of user decisions.
Supervised learning: Classification	It covers training and testing classification models on different datasets, including an introduction to key concepts; splitting the dataset into training and test sets; selecting algorithms; tuning hyperparameters; evaluating performance; and using the model to make new predictions.
Supervised learning: Regression	Similar to the classification topic, but focused on predicting continuous values, using algorithms, graphs, and metrics appropriate for regression tasks.
Quiz on supervised learning	A quiz with questions on classification and regression, featuring instant feedback and a random question selection.
Unsupervised learning: Clustering	This section introduces clustering concepts and allows users to customize algorithm hyperparameters before training to form clusters from the selected dataset, and provides a graphical visualization of the results.
Unsupervised learning: Dimension reduction	This section demonstrates how PCA reduces the dimensionality of the selected dataset, using static and dynamic images (GIFs) to illustrate key concepts, such as variance and principal components. Finally, the results from the dimensionality reduction are discussed and presented in graphs.
Quiz on unsupervised learning	It provides a quiz with questions on clustering and dimensionality reduction, featuring instant results and a random selection of questions.

To minimize the cognitive load associated with users' potential lack of mathematical proficiency, mathematical formulas are displayed only as supplementary explanations for users who wish to delve deeper into the subject. To mitigate issues related to programming code, various visual aids are distributed throughout the tool topics and steps, allowing the user to focus more on the no-code logic for solving the problems at hand. The main distinguishing feature of Visual-AM compared to the tools found in systematic mapping study by da Silva *et al.* (2024) is the pedagogical strategy adopted in its development, based on the concepts of active learning and metacognition discussed by Bransford *et al.* (2000). Based on these principles, the user is guided through the various stages of processing ML models by instructions presented in sequence and makes decisions using visual resources, such as drop-down menus, sliders, and buttons. Some of these features can be seen in Figure 1, which illustrates: (a) the selection of algorithms to be used in the regression task; (b) the prediction of the species of an iris flower in the classification task; (c) the selection of hyperparameters for training a classification model; and (d) the visualization of a 3D graph resulting from a clustering process. As users interact with the Visual-AM tool, it provides immediate feedback at certain points, such as during quizzes and the evaluation stages of supervised models. In other situations, graphical visualizations and numerical demonstrations of the results are used to

encourage users to reflect on the choices they made throughout the activities. This approach promotes knowledge-building through experimentation and critical analysis of results, aiming to achieve a deeper understanding of the fundamentals and practical implications of ML.

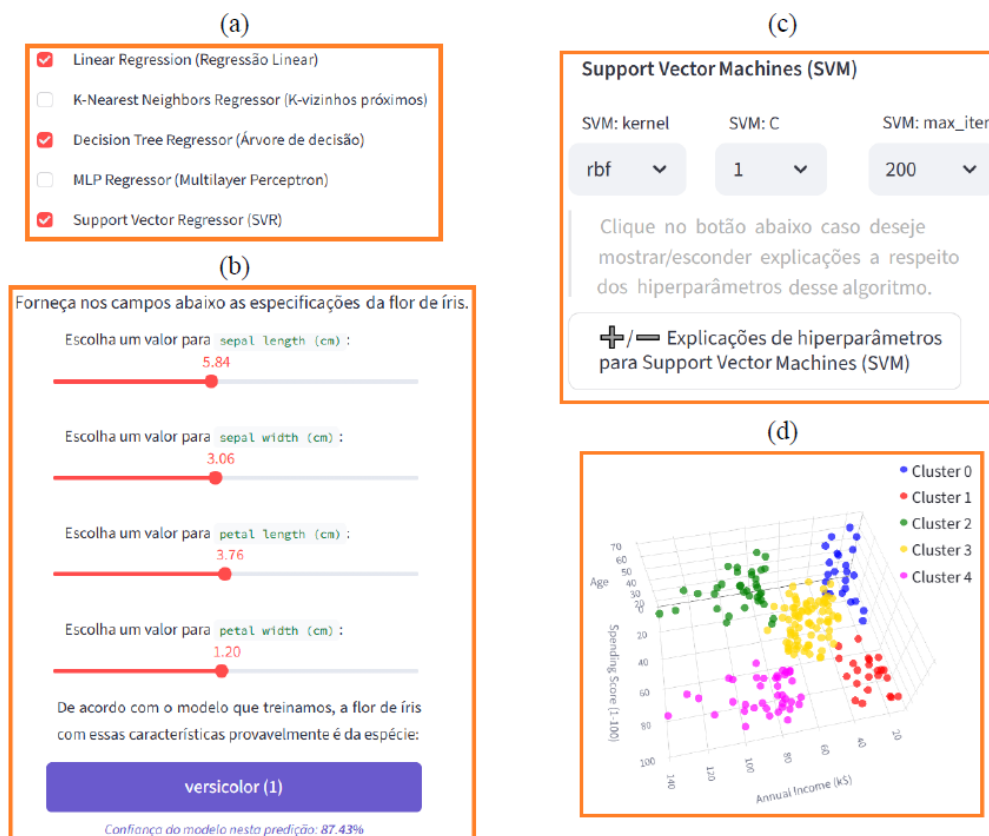


Figure 1. Demonstration of some tool features and visual elements. Source: The authors.

3.2 Participants and Description of the Method

After the tool was developed, 10 students in the Bioprocess Engineering course, who were enrolled in the elective discipline “Introduction to Data Science,” offered in the second semester of 2025 at Federal University of Itajubá, were invited to use it. The profile of this sample was well-suited to the tool purpose, as the students met the course prerequisites, having taken “Introduction to Bioprocess Engineering,” “Fundamentals of Programming,” and “Bioinformatics,” yet without the in-depth training in computational algorithms that students in traditional Computer Science courses typically possess.

Given the scarcity of standardized questionnaires for evaluating visual tools in computing research, it was deemed appropriate to adapt the questionnaires developed by Pereira and Seabra (2023) to evaluate the REA-LP tool. These questionnaires investigate respondents’ profiles, their experience using the tool, and their level of acceptance, aiming to evaluate its pedagogical characteristics in accordance with Gama’s Constructivist Learning Theory (2007) and Mayer’s Cognitive Theory of Multimedia Learning (2005). As a result of this adaptation, the Respondent Profile Identification Questionnaire (7 questions) and the Questionnaire of Reaction to the Use and Acceptance of the Tool (18 questions) were developed. To facilitate their distribution and administration, the questionnaires were made available to participants via the *Jotform* platform, allowing them to respond remotely and at their convenience.

It is important to emphasize that this research followed the ethical precepts determined by Resolution nº 510 [Brasil 2016], of April 7, 2016, and that, before using the tool, when volunteers were invited to participate in the study, they received an explanatory text about the objective of the research and the confidential character of the information collected. At the end of the explanation, those who agreed to participate in the research signed an Informed Consent Form. Next, participants completed the Profile Identification Questionnaire, which aimed to map participants' profiles by collecting information on access to technology, familiarity with educational tools, and prior experience with ML content. After using the tool, participants completed the Questionnaire of Reaction to the Use and Acceptance of the Tool, which aimed to assess students' reactions and gather their opinions on their experience using Visual-AM, addressing aspects such as the clarity of the ML content and the tool's potential to promote learning. To achieve these objectives, the questionnaires were designed using a mixed-methods (qualitative-quantitative) approach, allowing respondents to provide objective answers on a five-point Likert scale for most questions and open-ended qualitative insights via text fields. The questions from both questionnaires are presented in Table 2. In the Profile Identification Questionnaire, questions 1.2, 1.4-1.7 allowed participants to provide additional information at their discretion. All the questions in the Questionnaire of Reaction to the Use and Acceptance of the Tool allowed respondents to provide additional comments if they wished.

Table 2. Questions from the Profile Identification Questionnaire and the Questionnaire of Reaction to the Use and Acceptance of the Tool (continued). Source: The authors.

Focus	Nº	Question
Profile Identification Questionnaire	1.1	What is your gender? (Type: Multiple choice)
	1.2	Do you have Internet access at home? (Type: Multiple choice)
	1.3	Which of the following internet-connected electronic devices do you own? (Type: Multiple choice)
	1.4	Have you ever used a web-based visual tool for machine learning before this research? (Type: Multiple choice)
	1.5	How would you rate your knowledge of machine learning? (Type: Likert)
	1.6	Do you often use the Internet for your studies? (Type: Multiple choice)
	1.7	Do you like the idea of being able to access a web-based visual tool for studying machine learning from home at any time, whenever you need it, and at no cost? (Type: Likert)
Questionnaire of Reaction to the Use and Acceptance of the Tool	2.01	Is Visual-AM intuitive and easy to use? (Type: Likert)
	2.02	Has using Visual-AM sparked your interest in the machine learning topics it covers? (Type: Likert)
	2.03	Did using Visual-AM help you understand machine learning concepts? (Type: Likert)
	2.04	Do you feel confident using Visual-AM? (Type: Likert)
	2.05	Do you think you will be able to apply the knowledge you have gained from Visual-AM in your future work? (Type: Likert)
	2.06	After using Visual-AM, do you feel you have deepened your understanding of machine learning? (Type: Likert)
	2.07	How would you rate the visual elements provided by the tool (colors, images, GIFs, buttons, screen sizes, text size, etc.)? (Type: Likert)
	2.08	Did the Visual-AM charts, images, GIFs, and tables make it easier for you to study? (Type: Likert)
	2.09	Did you feel overwhelmed by the information Visual-AM presented through text, images, GIFs, charts, and tables? (Type: Likert)
	2.10	Have the animated images (GIFs) on Visual-AM made it easier to study machine learning concepts? (Type: Likert)
	2.11	Is the way the content on Visual-AM is presented and subsequently explained appropriate? (Type: Likert)
	2.12	Does Visual-AM present words, images, or information that are irrelevant to the study of machine learning concepts? (Type: Likert)
	2.13	Do you think Visual-AM presents content with excessive repetition of information? (Type: Likert)

	2.14	Which of the Internet-connected electronic devices did you use to access Visual-AM? (Type: Multiple choice)
	2.15	Would you use Visual-AM again? (Type: Likert)
	2.16	Would you like other subjects to use similar tools to study and reinforce the material covered in class? (Type: Likert)
	2.17	Would you like to share any general comments about using Visual-AM? (Type: Multiple choice)
	2.18	Have you noticed any issues and/or would you like to suggest improvements for Visual-AM? (Type: Multiple choice)

4. Results and Discussion

Using the Profile Identification Questionnaire, we characterized the participant sample in terms of general aspects, such as familiarity with technology and prior knowledge of ML. The objective responses to the questions in this questionnaire are presented in Figure 2.

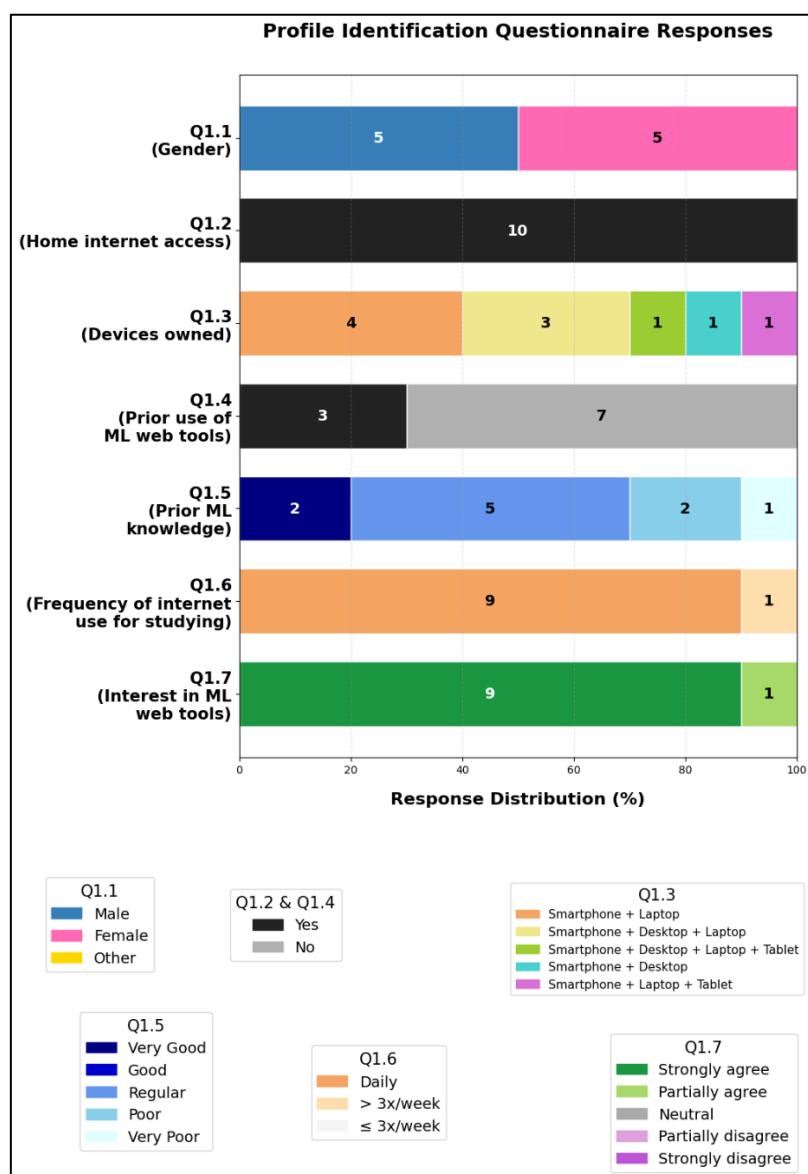


Figure 2. Summary of questions and answers from the Profile Identification Questionnaire. Source: The authors.

The Questionnaire of Reaction to the Use and Acceptance of the Tool collected respondents' opinions on Visual-AM, facilitating a systematic analysis of the tool

strengths and weaknesses. The quantitative responses to the questions in this questionnaire are presented in Figure 3.

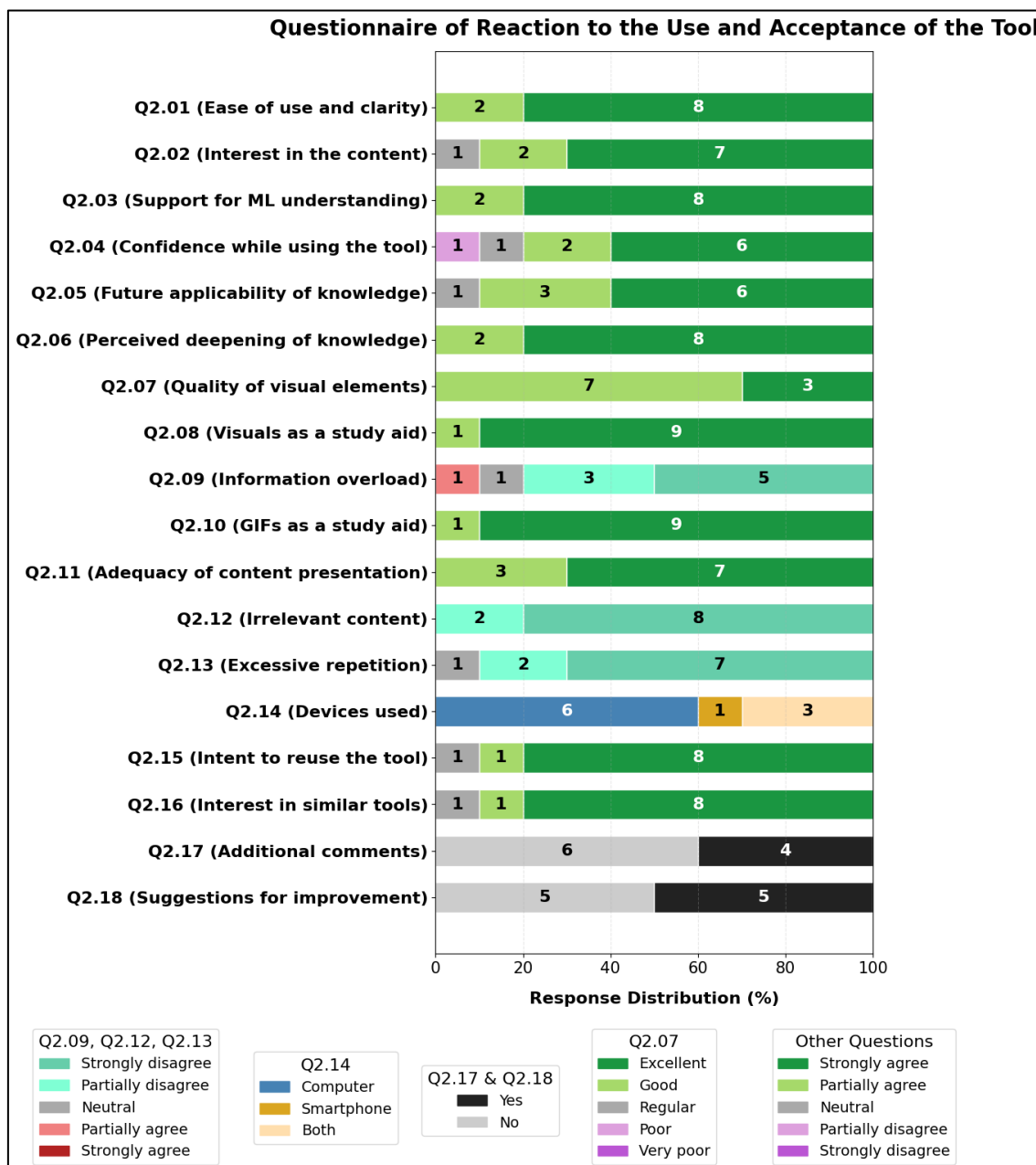


Figure 3. Summary of questions and answers from the Questionnaire of Reaction to the Use and Acceptance of the Tool. Source: The authors.

To quantify the questionnaire results, numerical values were assigned to the objective responses. First, it was determined that some responses to the Profile Identification Questionnaire were dichotomous. One such case is Question 1.4, which asked whether students had previously used visual tools to study ML, allowing only “Yes” or “No” as answers. Conversely, Questions 1.1 (“What is your gender?”) and 1.2 (“Do you have Internet access at home?”) provided for more than two response options in their original wording. However, in both cases, no participant selected the non-binary options, making the observed responses restricted to two categories. Therefore, these questions were also treated as dichotomous and numerically coded as 0 or 1. Questions 1.3, 2.14, 2.17, and 2.18, which provide only contextual and qualitative data, were analyzed

descriptively, without assigning numerical values to the responses. The remaining questions were coded using a five-point Likert scale, as shown in Table 3.

Questions	Coding					
	5	4	3	2	1	0
Q1.1	-	-	-	-	Female	Male
Q1.2 & Q1.4	-	-	-	-	Yes	No
Q1.5	Very good	Good	Regular	Poor	Very poor	-
Q1.6	Daily	> 3x / week	3x / week	< 3x / week	Never	-
Q2.09, Q2.12 & Q2.13	Strongly disagree	Partially disagree	Neutral	Partially agree	Strongly agree	-
Q2.07	Excellent	Good	Regular	Poor	Very poor	-
Q1.7, Q2.01 to Q2.08, Q2.10, Q2.11, Q.15 & Q2.16	Strongly agree	Partially agree	Neutral	Partially disagree	Strongly disagree	-

Table 3. Coding of questionnaire responses. Source: The authors.

After assigning values to the responses, potential correlations among them were analyzed using Spearman's rank correlation coefficient (ρ_s), which is appropriate for ordinal or dichotomous variables and for identifying nonlinear monotonic relationships without requiring data normality [Artusi *et al.* 2002; Sullivan and Artino Junior 2013]. However, prior to searching for correlations, analyses of response distributions were conducted to avoid spurious correlations. According to recommendations in the psychometric literature, items in which most responses are the same may be disregarded, as they tend to generate unstable correlations [Clark and Watson 1995]. Consequently, Questions 1.2, 1.6, 1.7, 2.08, and 2.10 were excluded from this analysis, as well as items of an exclusively contextual nature (Q1.3, Q2.14, Q2.17, and Q2.18). Based on the sample size ($n = 10$) and a significance level of 5% ($\alpha = 0.05$), only correlations with $\rho_s \geq 0.648$ were considered significant [Artusi *et al.* 2002], as presented in Table 4.

Table 4. Significant correlations between items. Source: The authors.

Question	Related Question	ρ_s	p-value	Possible Interpretation
Q1.4	Q1.5	0.694	0.0261	Students with prior experience using web-based visual tools for studying ML tend to consider their knowledge more advanced.
Q1.5	Q2.03	0.701	0.0239	Users with higher levels of knowledge tend to get more out of Visual-AM explanations.
Q2.01	Q2.15 and Q2.16	0.994	< 0.001	Students who found the tool more intuitive expressed a greater intention to use it again and showed greater interest in using similar tools in other courses.
Q2.02	Q2.03	0.807	0.0048	The interest generated by the tool appears to have helped users understand ML concepts.
Q2.04	Q2.05	0.675	0.0324	Confidence in using the tool tends to go hand in hand with the belief that the knowledge gained can be applied to future practice.
Q2.04	Q2.15 and Q2.16	0.660	0.0377	Users who feel more confident using the tool tend to want to use it again and have shown greater interest in using similar tools in other subjects.
Q2.15	Q2.16	1	< 0.001	The level of interest shown by the students in Visual-AM was the same as that shown in the possibility of using similar tools in studies of other disciplines.

To complement the interpretation of the results, the questions in the Questionnaire of Reaction to the Use and Acceptance of the Tool were organized into evaluative dimensions (constructs) proposed by the authors, grouping questions that address similar aspects. Thus, the questions were distributed across the following dimensions: "Information Flow," which covers questions regarding the clarity and appropriateness of the content to avoid unnecessary difficulties in studying; "Ease of Use," aimed at

assessing how intuitive users' interaction with the tool was; "Contribution of Visual Resources," which assesses the effectiveness of visual resources in representing ML concepts and facilitating understanding of the content; "Sense of Progress," which assesses students' self-perception regarding perceived progress in their studies; and "Engagement," which investigates the involvement and interest generated by the use of Visual-AM. The distribution of questions by dimension was as follows: "Information Flow": Questions 2.09, 2.11, 2.12, and 2.13; "Contribution of Visual Resources": Questions 2.07, 2.08, and 2.10; "Sense of Progress": Questions 2.03, 2.05, and 2.06; "Ease of Use": Questions 2.01 and 2.04; and "Engagement": Questions 2.02, 2.15, and 2.16. The remaining questions related to the context of access or to supplementary qualitative information in this questionnaire (2.14, 2.17, and 2.18) were grouped into a separate category titled "Contextual and Qualitative Data," providing information about the environment and user experience that aids in interpreting the preceding dimensions.

As Norman (2010) discusses, although individual Likert items may be considered ordinal, grouping them allows them to be treated as interval variables, thereby justifying the use of parametric statistics. Thus, the mean values were calculated for each evaluative dimension (Table 5), as shown in Figure 4, which displays 72-degree circular sectors representing each construct defined. In this representation, the radius of each circular sector is proportional to the mean score of its respective dimension.

Table 5. Average responses per participant, by dimension. Source: The authors.

Participant	Ease of Use	Engagement	Sense of Progress	Contribution of Visual Resources	Information Flow
1	5	5	4.67	4.33	4.75
2	4	4.67	4.33	4.67	4.5
3	5	5	5	5	5
4	4	4	5	4.67	4.75
5	4.5	5	4.33	5	5
6	5	5	5	4.67	4.5
7	3	3	4	4.33	4.25
8	5	4.67	4.67	4.67	4.75
9	5	5	5	5	4
10	5	5	5	4.67	4.25

The results indicated predominantly positive evaluations, with averages close to the maximum score across the five dimensions analyzed. The average score for the "Contribution of Visual Resources" dimension, along with participants' comments, suggests that graphic elements (such as images, buttons, and GIFs) contributed to the assimilation of ML concepts. Similarly, the dimensions "Sense of Progress," "Ease of Use," and "Informational Flow" indicate, respectively, that the tool fostered a sense of progress in studies, offered intuitive navigation, and organized content to reduce cognitive overload. The "Engagement" dimension indicates that Visual-AM was able to motivate users and stimulate interest in similar tools in other disciplines. One of the most significant findings of the correlation analysis was the positive association between prior knowledge of ML and perceived learning support, suggesting that users more familiar with the subject tend to make more in-depth use of the tool features. Among the limitations identified by the students, the lack of user progress storage across sessions stands out, along with suggestions to expand the content and include accessibility options for low-vision users. Finally, note that, although the sample size ($n = 10$) limits the generalizability of the results, it is consistent with recommendations in the literature for exploratory usability studies [Faulkner 2003; Macefield 2009]. The predominance of positive evaluations indicates good acceptance of the tool and suggests its potential as a

support for teaching ML. To illustrate the tool positive acceptance, Table 6 presents participants' comments.

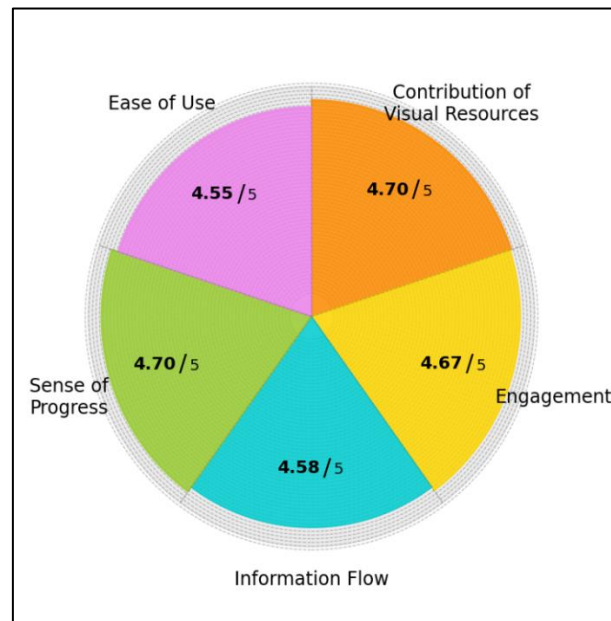


Figure 4. Graphical representation of the evaluative dimensions of Visual-AM. Source: The authors.

Table 6. Comments from the participants (continued). Source: The authors.

Question	Comment
2.01	"Visual-AM is well-organized and intuitive. The side menu makes it easy to find topics, and the content is organized into sections, which helps you follow along without getting lost. Overall, I was able to navigate the site and understand the flow without any difficulty."
2.02	"The way the content is presented – organized by topic and with a more visual, step-by-step approach – sparked my interest in learning more about machine learning concepts and exploring the next modules."
2.03	"The organization by topic and the step-by-step explanations made it easier to understand the concepts presented. The structure of the course helped reinforce key ideas and connect theory with examples."
2.04	"The navigation is clear, and the topic-based structure makes it easy to find what I need. I felt confident exploring the sections and following along with the content without any difficulty."
2.05	"The material covered provides a solid and practical foundation, and I believe I will be able to apply these concepts in future projects, such as interpreting results, choosing models, and implementing best practices in machine learning."
2.06	"I had already heard of some of these concepts, but Visual-AM introduced new material. The explanatory sections (optional) help to explore these topics in greater depth."
2.07	"The visual elements are excellent. The colors and visual identity are consistent, the layout is appealing and well-organized, and the text size makes it easy to read. The visual elements (images/GIFs and buttons) help keep the content light and easy to follow."
2.08	"I fully agree. The visual elements (graphs, images, GIFs, and tables) made it easier to understand the concepts and made studying more engaging. They help bring ideas to life that would be harder to grasp with text alone, and they also make it easier to compare results and retain the material."
2.09	"Overall, the layout is balanced and not overwhelming. Only in a few instances, when there is more content in a single section, would greater spacing or breaking it down into steps further enhance the experience."
2.10	"GIFs helped visualize processes and changes over time, making the explanation more intuitive and making it easier to understand concepts that would be more abstract if presented only in text."
2.11	"The option to expand or collapse items using the +/- button was a great addition."
2.12	"In general, the information is relevant and consistent with the study objective."
2.13	"Overall, the content is objective and well-organized."
2.15	"I would use Visual-AM again to help me review concepts and delve deeper into the material, since the tool is well-organized, clear, and makes it easy to study in a step-by-step manner."

2.16	<i>“Tools like these help reinforce what is covered in class, make studying more engaging, and encourage independent learning. In other subjects, visual and interactive resources could also improve understanding and retention.”</i>
2.17	<i>“Excellent work! I believe this tool has great potential to help students who are just beginning to explore machine learning. In addition, it is a great resource for reinforcing the material covered in class. Another important point is that, for students with a more visual learning style, Visual-AM can significantly help them consolidate what they have learned.”</i>
2.18	<i>“As an improvement, including more exercises and interactive demonstrations would help reinforce the learning even further.”</i>

4.1 Limitations

Some limitations must be considered in the interpretation of the results of this research. First, the small sample size limits the generalizability of the findings. Second, the evaluation focused on the participants' perceptions of the tool use, excluding objective performance measures or pre- and post-intervention tests that would allow measuring real learning gain. Third, the tool was developed using the *Streamlit Community Cloud* hosting platform, which is subject to operational restrictions observed at the time of this research, such as the absence of native mechanisms for persistence of progress between sessions (at the time of this research) and dependence on platform updates, which may affect its stability over time. Finally, the scope of Visual-AM is restricted to topics specific to classical ML, excluding approaches such as deep learning, reinforcement learning, and semi-supervised learning. These limitations do not invalidate the results but delimit the scope of the conclusions.

5. Final Considerations

The aim of this research was to make the study of ML fundamentals more accessible, especially for beginners, given the barriers associated with prior knowledge in areas such as mathematics and programming. As the main contribution and deliverable of this research, Visual-AM was developed – a visual, no-code web tool that enables the structured exploration of classical ML fundamentals. Based on a guided workflow and a visual approach, the tool enables practical exploration of models without coding. The development of the tool was based on a review of the literature on the fundamentals of ML and the challenges in this field, and was guided by the DSRM methodology, which enabled its evaluation in a real-world context. The results indicated predominantly positive evaluations across all the dimensions analyzed, suggesting that the tool offers adequate visual resources and promotes conceptual understanding, a sense of progress in studies, intuitive use, and user engagement. Although no objective pre- and post-intervention performance measures were conducted, the exploratory evidence obtained indicates the potential of Visual-AM as a teaching support resource.

For future work, we suggest conducting studies with larger sample sizes and across different educational contexts, as well as incorporating mechanisms to track user persistence and analyze user interactions. Among other possibilities for further research, the following stand out: integrating artificial intelligence techniques to generate personalized feedback, conducting experiments with objective learning assessment, expanding the tool scope to other ML techniques, and adapting it for other disciplines.

Statement on the Use of Artificial Intelligence

No artificial intelligence (AI) tools or AI-assisted technologies were used in the drafting, editing, or revising of this manuscript.

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