

From industrial data to business decisions: Industrial case studies as teaching instruments in interdisciplinary analytics education

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Abstract. *This paper analyses industrial problems as teaching instruments in interdisciplinary analytics education, based on 14 student project reports from two industrial case studies: SICK Mobilisis (AI-based fuel-event detection from vehicle telemetry data) and Emil Frey Digital (digital vehicle sales optimisation). Reports were analysed using a qualitative coding framework covering business-process understanding, analytical-unit construction, target design, feature availability, validation, metric interpretation, decision support, implementation, and risk. Students usually completed expected sections but had more difficulty connecting them into a coherent process from data to decision, particularly regarding analytical-unit definition, leakage-aware feature selection, validation design, and linking model outputs to business decisions.*

Keywords. data science education, business analytics, work-based learning, project-based learning, industrial case studies, decision support, data leakage, AHP

1 Introduction

Data science and business analytics education often introduces students to predictive models, evaluation metrics, and standard data-preparation procedures. These elements are necessary, but they are not sufficient for applied industrial analytics (Brüngel, Rückert, & Friedrich, 2020; De Veaux et al., 2017; Ramasamy & Ramamoorthy, 2023). In real projects, the analytical task is rarely given in a clean and predefined form. Students have to understand the process that generates the data, define the analytical unit, construct a meaningful target variable, identify which features are available at the moment of decision, choose an appropriate validation design, and interpret model results in re-

lation to business risk or economic value. This corresponds to the broader logic of end-to-end analytics processes, where business understanding, data understanding, data preparation, modelling, evaluation, and deployment-oriented interpretation are treated as connected phases rather than isolated technical steps (Chapman et al., 2000).

This problem is especially visible in project-based and case-based data science education. Industrial projects can help students develop practical skills, teamwork, and problem-solving abilities that are difficult to obtain from isolated algorithmic exercises (Brüngel et al., 2020; Ramasamy & Ramamoorthy, 2023). However, an authentic industrial problem does not by itself ensure methodological understanding. A student team may build a model and report standard evaluation metrics even when the target does not correspond to the business decision, the feature set contains information unavailable at prediction time, or the validation design does not reflect future use. The central limitation is then the transition from the business process to the analytical task rather than model selection alone. Work-based learning (WBL) provides a useful lens for this setting because it connects academic learning with professional practice through real-world and industry-oriented activities (Perusso & Wagenaar, 2021; Rienties, Divjak, Iniesto, Pažur Aničić, & Zizak, 2023).

This paper examines the transition from an educational setting to a work-oriented analytics setting through two industrial case studies used in an interdisciplinary project-based course. The student teams included students from information systems and business/economics study programmes, which made the projects suitable for analysing how technical modelling, business-process understanding, and decision-support reasoning are connected. The first case, provided by SICK Mobilisis, involved sensor-based ve-

hicle telemetry data for AI-based fuel-event detection. The second case, provided by Emil Frey Digital, involved business and sales-process data for the optimisation of digital vehicle sales through analytical recommendations. The two cases differ in domain and data structure. The SICK Mobilis case required students to reason about temporal sensor data, rare events, false alarms, missed detections, and the difference between row-level classification and event-level detection. The Emil Frey Digital case required students to reason about a sales funnel, linked business tables, marketplace attribution, target construction, return on investment, conversion, and the connection between machine learning outputs and multi-criteria decision-making. A central difficulty in both cases is that the analytical dataset is not given. It has to be constructed from the available data and aligned with the intended decision. If features are derived from later stages of the process, or if the same entity appears in both training and test data, model performance can become overly optimistic because of leakage (Apicella, Isgrò, & Prevete, 2025; Kapoor & Narayanan, 2023; Sasse et al., 2025). Therefore, leakage and validation problems are not only technical mistakes. In student projects, they also indicate the extent to which students understand the temporal, entity-based, and process-based structure of the industrial problem.

The decision-support part introduces a second difficulty. Predictive models estimate classes, probabilities, or scores, but these outputs still have to be translated into alternatives, criteria, risks, and business actions. Multi-criteria decision-making methods such as the Analytic Hierarchy Process (AHP) can support this translation because they require explicit criteria and priorities (Saaty, 1980). However, AHP can also remain detached from the predictive model if the criteria are not linked to model outputs, feature importance, business risk, or economic value. This is particularly important in interdisciplinary analytics education, where students are expected to connect information-systems modelling with economic decision-making (Pang & Quek, 2026).

The main argument of this paper is that real industrial case studies are useful not only because they provide authentic data, but because they expose the methodological transitions that students must learn to manage. In simplified classroom datasets, the row, target variable, feature set, validation design, and interpretation of metrics are often already defined. In industrial data, these elements have to be justified. For this reason, student reports can be analysed as evidence of how students understand applied analytics as a methodological and decision-oriented process.

This paper contributes to data science and business analytics education by analysing how student teams translate real industrial problems into analytical tasks and business decisions. The study uses 14 student project reports from the two industrial case studies and

codes them according to methodological transitions that are often hidden in simplified classroom datasets, including business-process understanding, analytical-unit construction, target design, feature availability, validation design, metric interpretation, and decision support. The reports are analysed as empirical evidence of how students reason through real industrial analytics problems. The analysis identifies recurring strengths, weaknesses, and teaching implications, with a particular focus on the transition from business process to analytical task and from model output to business decision. In addition, this study addresses the following research questions:

- RQ1: How do students describe and understand the business process in industrial analytics projects?
- RQ2: How do students construct the analytical dataset, target variable, and features?
- RQ3: Which modelling and validation choices do students most frequently make?
- RQ4: How do students interpret model results in relation to the business problem and economic decision?
- RQ5: Which teaching interventions can be derived from the observed patterns?

The remainder of the paper is organised as follows. Section 2 reviews related literature. Section 3 describes the educational setting, case studies, corpus, and coding framework. Section 4 presents the findings. Finally, Section 5 discusses implications for analytics education and concludes the paper.

2 Related Work

2.1 Project-based and work-based learning with real industrial data

Project-based and case-based learning are frequently used in data science and business analytics education because they expose students to tasks that are closer to professional analytical practice than isolated algorithmic exercises (Brünger et al., 2020; Raschka, 2022). In such settings, students have to formulate the problem, understand the available data, prepare the dataset, select methods, evaluate results, and communicate recommendations. This is important because professional data science work is usually carried out with incomplete, noisy, context-dependent, and process-generated data rather than with clean benchmark datasets (Chapman et al., 2000; Kutzias, Dukino, Kötter, & Kett, 2023).

Work-based learning extends this logic by placing the learning activity closer to professional practice. It usually includes projects, workplace simulations, industry collaboration, or entrepreneurship-oriented activities in which students develop practical knowledge

through real-world challenges (Perusso & Wagenaar, 2021). This is especially relevant for interdisciplinary analytics education because industrial problems require more than technical modelling. Students have to understand organisational processes, communicate with different stakeholders, work in teams, and justify analytical choices in relation to business value. Recent work on online WBL also shows that work-based approaches can support the connection between academic learning, digital competence, and professional contexts (Rienties et al., 2023). In the present study, the industrial cases function as a WBL environment because students worked with real company problems, raw process-generated data, and decision-oriented outputs rather than with predefined classroom exercises.

Previous work has emphasised the need to align data-centric curricula with industry requirements. Authors in (Ramasamy & Ramamoorthy, 2023) argue that data-centric project curricula can support the development of an industry-ready workforce by connecting technical learning with current analytics requirements. Similarly, in (Brüngel et al., 2020) authors presented project-based learning in a machine learning course with differentiated industrial projects and show that industrial project settings can support both practical and social skills needed for real-world problem solving. Work on labour-market alignment also indicates that higher education curricula may lag behind changing industry needs, especially in applied technical skills and interdisciplinary problem solving (Shiwei & Abas, 2026). More general evidence on project-based learning also supports its positive role in student learning outcomes (Zhang & Ma, 2023). In machine learning education, hands-on project work has been used to connect model development with experimental design, reporting, and communication of results (Raschka, 2022).

These studies support the use of industrial problems, project-based learning, and WBL in data science and business analytics education. However, they mostly focus on curriculum design, industry readiness, skill alignment, or the general value of authentic learning. Less attention is given to what student project reports reveal about the specific methodological transitions that students have to manage when they work with raw industrial data. This is the focus of the present study: the reports are used as evidence of how students move from professional practice to analytical formulation, and from model outputs to decision-oriented recommendations.

2.2 Leakage, validation, and feature availability as learning challenges

A central difficulty in applied machine learning is that technically correct pipelines may still produce invalid conclusions if the data are not split, prepared, or interpreted according to the real prediction setting (Kapoor

& Narayanan, 2023; Sasse et al., 2025). Data leakage occurs when information that would not be available in a real use case enters the training or evaluation process. This can lead to overly optimistic performance estimates and models that fail to generalise (Apicella et al., 2025; Kapoor & Narayanan, 2023; Sasse et al., 2025). Recent work shows that leakage is not a marginal issue. In (Apicella et al., 2025), the authors discuss leakage risks in machine learning and transfer learning and warn against “push the button” use of machine learning tools without sufficient methodological control. Moreover, research in (Sasse et al., 2025) provides an overview of leakage scenarios in supervised machine learning and shows that leakage may arise from overlap, preprocessing, feature construction, or evaluation design. The importance of proper data representation is emphasized in (Kapoor & Narayanan, 2023), where authors connect leakage with the reproducibility crisis in machine-learning-based science and show that leakage has affected a wide range of research fields, especially education. Tool-oriented work, such as LeakageDetector 2.0, further shows that leakage can occur inside practical Jupyter-driven machine learning workflows (Truong et al., 2025).

Applied analytics projects require a sequence of connected methodological decisions, from business understanding and data preparation to modelling, evaluation, and deployment-oriented interpretation. Cross-Industry Standard Process for Data Mining provided a classical process view of data mining projects (Chapman et al., 2000), while more recent comparisons of data science process models show that such frameworks remain relevant for structuring data science work across project phases (Kutziyas et al., 2023). For educational projects, this process perspective is important because it makes visible that model training is only one part of the analytical task. Students also have to define the unit of analysis, construct the target variable, decide which features are valid, and select an evaluation design that corresponds to the intended use of the model (Chapman et al., 2000; Kutziyas et al., 2023). In educational projects, leakage is not only a technical problem, but also a learning signal. If students use features that are generated after the decision point, or if they split data in a way that allows the same entity or future information to appear in both training and test data, this indicates a weak understanding of the temporal or process structure of the industrial problem (Apicella et al., 2025; Kapoor & Narayanan, 2023; Sasse et al., 2025).

2.3 Business analytics, case-based learning, and decision support

Business analytics education requires students to connect analytical outputs with decisions, risks, costs, and organisational value. A predictive model is useful only if its output can be translated into an action, recom-

mentation, or decision criterion. For this reason, case-based and problem-driven approaches are especially relevant in business analytics education. Research on case-based learning suggests that real-life scenarios can support analytical reasoning, deeper cognitive processing, and decision-making skills (Silitubun, Mustaji, & Dewi, 2025). More generally, a meta-analysis of problem-based, project-based, and case-based learning found a positive effect of student-centred, problem-driven methods on student motivation (Wijnia, Noordzij, Arends, Rikers, & Loyens, 2024). These findings support the use of authentic problems as teaching instruments, especially when the goal is not only technical knowledge but also the ability to reason about decisions.

Industry-oriented business analytics programmes also emphasise the need to bridge academic learning and organisational practice. The authors in (Pang & Quek, 2026) describe a structured industry-collaboration framework in business analytics education and argue that industry-ready analytics professionals require both analytical competence and exposure to practical organisational problems. This is consistent with the central premise of the present study: students should not only build models, but also explain how model outputs support decisions. Decision-support literature similarly emphasises that analytical results should be connected to alternatives, criteria, organisational goals, and decision processes rather than treated as isolated model outputs (Turban, Sharda, & Delen, 2010). Multi-criteria decision-making methods provide a structured way to compare alternatives when several criteria have to be considered at the same time (Velasquez & Hester, 2013). In this context, AHP is relevant because it requires alternatives, criteria, and priorities to be made explicit (Saaty, 1980; Velasquez & Hester, 2013). However, decision-support methods do not automatically integrate predictive modelling with business decision-making. If decision criteria are not connected to model outputs, feature importance, business risk, or economic value, the decision-support component remains separate from the analytical model. This is a central issue in interdisciplinary student projects: students may build a model and also perform multi-criteria decision-making, but still fail to explain how prediction, criteria, alternatives, and economic value are connected.

3 Methodology

3.1 Educational context

The empirical material consisted of student project reports produced as part of interdisciplinary projects at the University of Zagreb Faculty of Organization and Informatics (UNIZG FOI). The student teams included students from Artificial Intelligence for Business Applications (AIBA), within the Information and

Business Systems (IBS) study programme, and Business Decision Making (BDM), within the Economics of Entrepreneurship (EE) study programme. This made the setting suitable for connecting technical modelling with business-oriented interpretation. Since the projects were based on real industrial problems and embedded in student assessment, the setting can be interpreted as a work-based learning environment. The industrial partners provided real business problems and process-generated data, while the student teams were expected to transform these problems into analytical and decision-support tasks. This required students to analyse a real business case, describe the company and its market environment, examine the available data, prepare the dataset, construct analytical features, select and evaluate predictive models, compare model-based results with multi-criteria decision-making, and propose an implementation-oriented business recommendation. Thus, the reports combined data science, information systems, business analytics, and economic decision-making.

All reports followed a common documentation template. The required sections included company description, product or service description, market and competitor analysis, problem description, dataset description, exploratory data analysis, data-quality assessment, data preparation, modelling, AHP-based criteria weighting, comparison between sensitivity analysis and AHP weights, evaluation, alternatives, implementation risks, ethical reflection, implementation planning, and final recommendations. This common structure made the reports comparable and allowed the analysis to focus not only on the presence of project components, but also on how students connected them into a coherent analytical and decision-support process.

3.2 Case studies

The first case study was provided by SICK Mobilisis, a company that develops intelligent fleet management, traffic monitoring, and parking management solutions. The case focused on AI-based fuel-event detection using vehicle telemetry data. The data type was sensor-based, telemetry-oriented, and temporal. The main educational challenge was that students had to understand the difference between classifying individual records and detecting operational events. A single telemetry record is not necessarily equivalent to a fuel event. A suspicious event may appear as a sequence of measurements, a fuel-level change over time, a threshold crossing, or a pattern that has to be interpreted in relation to vehicle movement and operational context. Therefore, students had to reason about time, rare events, false alarms, missed detections, event construction, and operational use. The SICK Mobilisis reports generally included standard sections on the company, products, market, problem, data, data quality, preparation, modelling, and AHP. Some reports also included more ad-

vanced modelling components, such as Random Forest, XGBoost, multilayer perceptrons (MLP), recurrent neural networks (RNN), gated recurrent units (GRU), bidirectional long short-term memory (LSTM), conditional random field (CRF)-based extensions, threshold tuning, and production-oriented testing. These elements made the case useful for analysing how students respond to temporal and sensor-driven industrial problems.

The second case study was provided by Emil Frey Digital, a company that develops digital solutions for car sales and after-sales processes. The case focused on the optimisation of digital used-vehicle sales through analytical recommendations. The data reflected a business process involving vehicle publishing, marketplace platforms, customer leads, offers, and contracts. The main educational challenge was that students had to understand the sales funnel, construct a valid unit of analysis, define a meaningful target variable, reason about attribution of sales to platforms, and connect model results with return on investment, conversion, and decision support. The Emil Frey Digital reports followed a structure similar to the SICK Mobilis reports. They included modelling, sensitivity analysis, AHP, alternatives, risk analysis, ethical reflection, and implementation planning. However, the methodological challenge was different. Students had to determine what one row represented: a vehicle, a vehicle-marketplace combination, a published advertisement, a lead, an offer, or a contract-related outcome. This choice determined the meaning of the target variable, the availability of predictors, the validation design, and the interpretation of the model as a recommendation tool.

3.3 Corpus

Table 1. Corpus summary

Element	Value
Student reports	14
Industrial cases	2
SICK Mobilis reports	7
Emil Frey Digital reports	7
Listed students	122
Students in SICK Mobilis teams	60
Students in Emil Frey Digital teams	62
Typical team size	8–9
Report-length range	14–146 pages
Approx. corpus size	660 pages
Report type	Business, analytics, AHP

The corpus consisted of 14 student project reports produced by interdisciplinary student teams. Seven reports addressed the SICK Mobilis fuel-event detection case and seven reports addressed the Emil Frey Digital sales-optimisation case. Based on the cover pages, the reports involved 122 listed students, 52 from AIBA and 70 from BDM, with teams typically consisting of eight or nine members. Table 1 summarises the corpus. The reports varied in the methodological detail provided across the coding dimensions, which made it possible to identify recurring patterns. Grades were

neither collected nor used as coding variables, and the analysis did not evaluate or rank individual teams.

The reports were treated as the primary unit of analysis. Individual report sections were used as secondary analytical units when coding specific methodological and pedagogical dimensions. These sections included the problem description, dataset description, data-quality assessment, data preparation, modelling, validation, sensitivity analysis, AHP-based decision support, evaluation, risk analysis, ethical reflection, and implementation planning. The aim was not to grade individual student teams, but to identify recurring learning patterns and methodological difficulties that appear when students work with real industrial data. Because all reports followed the same assignment template, the coding focused on differences in methodological reasoning instead of differences in report structure.

3.4 Coding framework and scale

A qualitative coding framework was developed to analyse how students translated industrial problems into analytical projects. The framework followed the expected stages of an applied analytics project: understanding the business process, constructing the analytical dataset, defining the target, preparing the data, selecting and validating models, interpreting metrics, and connecting analytical results to a decision. The coding framework included eleven dimensions, shown in Table 2. Each dimension captured a specific transition that students had to manage. Business-process understanding captured the transition from a general company description to the operational process that generated the data. Target design captured the transition from a business problem to a measurable outcome. Validation design captured the transition from a trained model to a credible estimate of future performance. AHP and decision support captured the transition from predictive modelling to economic or managerial decision-making. Each report was assessed independently on every coding dimension using the four-point ordinal scale shown in Table 3. Evidence was taken from the report sections relevant to that dimension rather than from the report’s overall presentation or grade. The scale was designed for descriptive comparison rather than statistical hypothesis testing. The authors reviewed the reports and resolved ambiguous cases through discussion and consensus. Higher scores indicated a clearer connection between the coded element, case-specific evidence, methodological reasoning, and the business decision.

For example, in the target-design dimension, a report received a score of 0 if the target variable was not clear. It received a score of 1 if the target was named but its business meaning was not explained. It received a score of 2 if the target was explained but still involved potential leakage or weak alignment with the decision.

Table 2. Coding dimensions

Dimension	Focus
Business process	Understanding of the process and decision context.
Analytical unit	Definition of row, event, vehicle, advertisement, lead, offer, or contract.
Target design	Clarity and business validity of the target variable.
Feature availability	Availability of predictors at the moment of decision and leakage risk.
Data preparation	Missing values, duplicates, outliers, feature construction, and integration.
Modelling choice	Suitability of selected models for the data structure and task.
Validation design	Appropriateness of random, temporal, group-based, or event-level validation.
Metric interpretation	Connection between model metrics and business or operational risk.
AHP / decision support	Connection between criteria, model outputs, alternatives, and economic decisions.
Implementation	Explanation of how the proposed solution could be used in practice.
Ethics / risk	Specificity of ethical and implementation risks.

Table 3. Coding scale

Score	Meaning
0	The element is not present.
1	The element is present only superficially or generically.
2	The element is partially developed and supported by case-specific examples.
3	The element is methodologically clear and connected to the business decision.

It received a score of 3 if the target was clearly connected to the business process, the moment of decision, and the evaluation design.

The same scoring logic was applied within the other dimensions. For validation design, the scale progressed from no stated design (0), through an unjustified generic split (1) and a partly justified but incomplete design (2), to a temporal, group-based, per-entity, or event-level design aligned with intended use (3). For metric interpretation, it progressed from no interpretation (0), through generic reporting (1) and partial case-specific interpretation (2), to an explicit connection between metrics and operational or economic consequences (3). For AHP and decision support, it progressed from absence (0), through a separate or generic AHP exercise (1), partial linkage to analytical evidence (2), and an explicit connection among model outputs, criteria, alternatives, and business decisions (3).

The scale did not define binary or global “strong report” and “weak report” classes. Scores were not aggregated into an overall report-quality label, and no threshold was used to classify an entire report. Instead, every dimension retained its own score. A report could therefore provide methodologically clear evidence in one dimension, such as business-process understanding, while providing only generic evidence in another, such as validation. Such mixed profiles were expected and were central to the analysis because they revealed which transitions were understood and which still required instructional support.

3.5 Qualitative comparison

The analysis followed a comparative qualitative design. First, each report was reviewed according to the coding dimensions. Second, recurring patterns were identified within each case group. Third, the two case groups were compared to determine how the nature of the in-

dustrial problem shaped student reasoning.

The comparison was structured around four analytical questions. First, how did students understand the business process behind the data? Second, how did they construct the analytical dataset and define the unit of analysis? Third, how did they choose models and validation procedures? Fourth, how did they interpret results and connect them to decision support?

This design allowed the analysis to move beyond individual report quality and focus on the pedagogical value of real industrial cases. The two cases created different learning pressures. The SICK Mobilis case exposed problems related to temporal data, rare events, event construction, and operational alarms. The Emil Frey Digital case exposed problems related to business-process data, target construction, attribution, recommendation, and economic evaluation.

4 Results

Table 4 summarises the main patterns observed in the reports. These frequencies are binary indicators of explicit evidence and are reported separately from the four-point dimensional scores. Formal sections were counted when the required report component was present. A methodological-integration pattern was counted only when the report explicitly stated or justified the relevant connection to the business process, analytical unit, target definition, validation design, model interpretation, or decision-support logic. The totals therefore describe evidence for individual patterns; they do not classify complete reports. A report could be counted in one row and not in another, producing mixed dimensional profiles. Fig. 1 visualises the contrast between formal completion and methodological integration.

4.1 Business-process understanding

Students generally described the companies, products, services, markets, competitors, and SWOT analyses in sufficient detail. However, the operational process behind the data was less consistently explained. In the SICK Mobilis case, most reports identified fuel-event detection as the core problem. Reports that clearly represented the process treated it as a temporal telemetry

Table 4. Observed methodological patterns in the analysed reports

Observed pattern	SICK Mobilisis	Emil Frey Digital	Total
Formal data-quality section included	7/7	7/7	14/14
Data-preparation section included	7/7	7/7	14/14
Modelling section included	7/7	7/7	14/14
AHP or decision-support section included	7/7	7/7	14/14
Risk, ethics, and implementation sections included	7/7	7/7	14/14
Analytical unit explicitly discussed	3/7	3/7	6/14
Target variable explicitly linked to the business decision	4/7	3/7	7/14
Feature availability or leakage explicitly discussed	3/7	3/7	6/14
Validation justified beyond a generic random split	4/7	3/7	7/14
Metrics linked to operational or economic risk	3/7	3/7	6/14
AHP criteria explicitly connected to model outputs or feature importance	3/7	3/7	6/14
Concrete deployment or operational-use scenario included	4/7	3/7	7/14

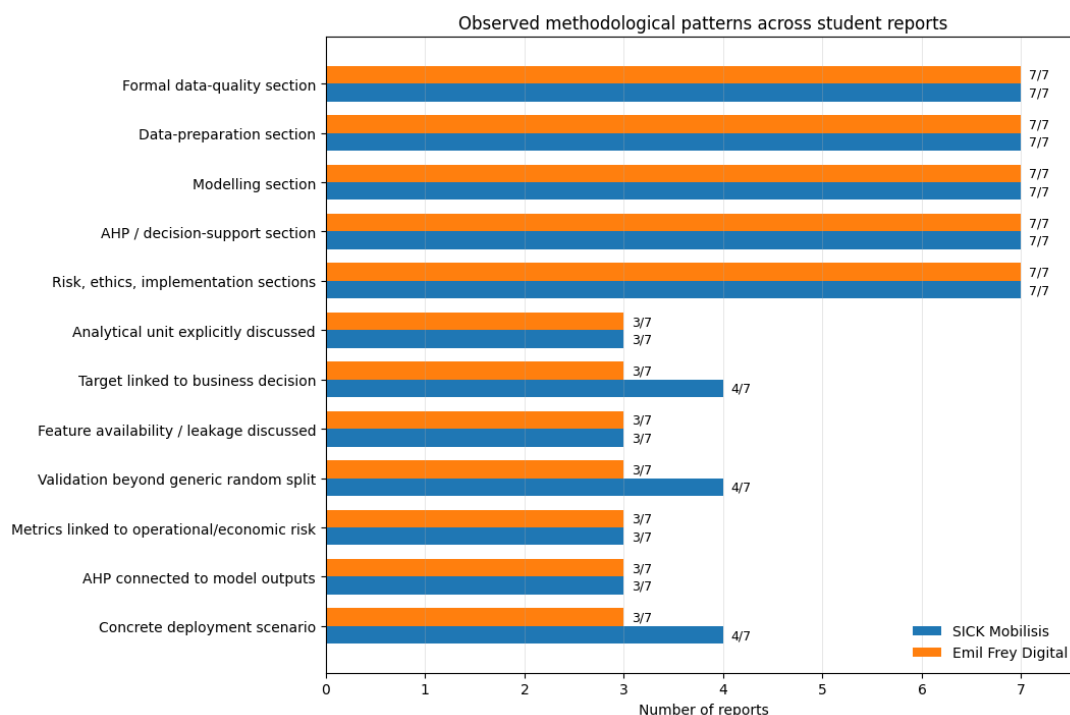


Figure 1. Observed methodological patterns across the 14 student reports. Formal project sections were present in all reports, while methodological integration was less consistent, especially for analytical-unit definition, feature availability, metric interpretation, and the connection between predictive modelling and AHP-based decision support.

problem in which an event may involve a sequence of measurements or a fuel-level change over time. Other reports treated the task mainly as ordinary row-level classification and did not explain how individual predictions would become operational alarms. In the Emil Frey Digital case, most reports described digital vehicle sales and online marketplaces, but their treatment of the sales funnel varied. Some reports treated the data as a standard tabular classification dataset. Others explicitly recognised that publishing, leads, offers, contracts, and sales outcomes occur at different stages and cannot all be used at the same decision point. Across both cases, company-context descriptions were more complete than explanations of the process logic connecting data, prediction, and action.

4.2 Construction of the analytical dataset

The analytical unit was one of the main difficulties. Several reports used the available rows as given, whereas others explicitly discussed what the rows should represent for the intended decision.

In the SICK Mobilisis case, the raw unit was usually a telemetry record, but the business unit was a fuel event. This created a mismatch between row-level modelling and event-level interpretation. Some reports addressed this mismatch by considering time windows, vehicle trajectories, sequences, thresholding, or alarm construction. Others reported classification metrics without explaining how record-level predictions would be aggregated into an event.

In the Emil Frey Digital case, the unit of analysis was less obvious because the data came from several linked business tables. A row could represent a vehicle,

a vehicle-marketplace combination, an advertisement, a lead, an offer, or a contract. Reports that did not define this unit clearly were more exposed to repeated-vehicle leakage, target ambiguity, and the use of post-publication information in pre-publication recommendations.

The cross-case pattern is simple: in industrial data, the row is not self-evident. It has to be constructed according to the decision that the model is expected to support.

4.3 Modelling and validation choices

The reports used a wide range of models. In the SICK Mobilis case, teams used classical tabular models such as Random Forest and XGBoost, as well as MLP, RNN, GRU, LSTM, and CRF-based variants. Some reports connected these choices to sequence construction, temporal order, threshold selection, and event interpretation. In others, more complex models were used without a clear explanation of their suitability for the telemetry problem.

In the Emil Frey Digital case, tabular models such as logistic regression, Random Forest, XGBoost, Naive Bayes, and MLP were generally appropriate for the structured business data. The main problem was not the choice of algorithm, but the target. Predicting a historical marketplace label does not necessarily recommend the best marketplace. Predicting sale probability also does not directly determine return on advertising investment or marketing-budget allocation.

Validation was a recurring difficulty. Some reports used generic random splits, whereas others recognised the need for temporal, group-based, or process-aware validation. In the SICK Mobilis case, validation should respect temporal order and event structure. In the Emil Frey Digital case, it should avoid placing records of the same vehicle in both training and test data. Validation design therefore provided a useful indicator of process understanding.

4.4 Feature availability and leakage

Feature availability was one of the clearest indicators of methodological understanding. Most reports included data preparation and model evaluation, but fewer reports explicitly discussed which variables would be available at the moment when the model would be used. This distinction was important in both cases because some variables were generated after the relevant business decision or were linked to the same entity across multiple records.

In the SICK Mobilis case, the main leakage risk was connected to temporal order and event construction. A model for fuel-event detection should not use information that becomes available only after the event has unfolded. Some reports recognised this problem by discussing chronological splits, per-vehicle valida-

tion, threshold selection, sequence construction, or the removal of variables that could reveal the target too directly. Other reports treated the data mainly as independent tabular records, which made the validation design less aligned with the intended operational use.

In the Emil Frey Digital case, the leakage risk was connected to the sales funnel. Some variables related to leads, offers, contracts, or later customer actions may be useful for analysing historical sales performance, but they are not necessarily available when the system has to recommend where or how to publish a vehicle advertisement. Some reports carefully separated publishing-time information from post-publication outcomes. Others used later-stage variables as predictors, which may improve apparent model performance but weaken the validity of the recommendation task.

Across both cases, leakage was therefore not only a technical data-splitting problem. It indicated the extent to which students understood the temporal and process-based structure of the industrial task. Reports that explicitly discussed feature availability, entity overlap, chronological order, or the moment of decision also tended to provide more credible validation and more meaningful business interpretation.

4.5 Interpretation and decision support

Most reports included model metrics and an AHP-based decision-support component. The main difference was how well these parts were connected.

In the SICK Mobilis case, some reports interpreted metrics through operational risk. Precision, recall, F1-score, and threshold choice were connected to false alarms, missed fuel withdrawals, real-time monitoring, or inspection decisions. Other reports presented the metrics without explaining their operational consequences. In the Emil Frey Digital case, some reports linked model outputs to conversion, time-to-sale, advertising cost, lead quality, or return on investment. Others treated feature importance or prediction accuracy as sufficient for a marketplace recommendation without explaining its economic meaning.

AHP was present in the project structure, but it was not always integrated with the predictive model. In some reports, AHP appeared as a separate economic exercise. In others, model results, feature importance, operational criteria, and business alternatives were discussed together. This integration is important because AHP becomes more educationally meaningful when its criteria are justified by model evidence, domain constraints, and economic consequences rather than by generic preferences alone. Overall, the least developed transition was not from data preparation to modelling, but from model performance to a justified business decision.

4.6 Summary of findings by research question

For **RQ1**, students generally described the companies, markets, and business problems in sufficient detail. However, they less consistently explained the operational process that generated the data and determined the analytical task.

For **RQ2**, the main difficulties concerned the analytical unit, target variable, and feature availability. The reports did not always distinguish telemetry records from fuel events or clearly determine what a row represented: a vehicle, advertisement, marketplace entry, lead, offer, or contract. Variables generated after the decision point also created potential leakage.

For **RQ3**, most teams used appropriate supervised-learning models, including Random Forest, XGBoost, logistic regression, Naive Bayes, MLP, and sequence-oriented models. Model selection was generally less problematic than validation. Several reports used generic random splits, while others recognised the need for temporal, group-based, per-vehicle, or process-aware validation.

For **RQ4**, students usually reported standard model-evaluation metrics, but did not always connect them to operational or economic consequences. The clearest interpretations related false alarms and missed events to operational risk or connected model outputs to conversion, advertising cost, return on investment, lead quality, and time-to-sale.

For **RQ5**, the findings indicate that students should explicitly define the analytical unit, identify the moment of decision, review feature availability, justify the validation design, interpret metrics in relation to business consequences, and connect predictive modelling with AHP-based decision support.

4.7 Pedagogical implications

The observed patterns suggest several pedagogical implications for interdisciplinary analytics education:

- **Define the analytical unit before modelling.** Students should explicitly state if the unit of analysis is a record, event, vehicle, advertisement, lead, offer, contract, or another process-specific object. This prevents them from treating the available row in the dataset as automatically suitable for prediction or decision-making.
- **Use WBL checkpoints to connect academic and professional reasoning.** Industrial analytics projects should include moments where students explicitly relate their analytical choices to the professional context of use. This includes explaining how raw company data become an analytical dataset, how model outputs support a business action, and how recommendations would be communicated to non-technical stakeholders.

- **Introduce the moment of decision as a mandatory checkpoint.** Before selecting features, students should identify when the model is expected to be used and which variables are available at that point. This can reduce leakage and help students distinguish between historical explanation and usable prediction.
- **Teach validation design as part of problem formulation.** Students should justify if a random, temporal, group-based, per-entity, or event-level split is appropriate for the intended use of the model. This is especially important when repeated entities, temporal order, or process stages make random splits misleading.
- **Connect model metrics to operational or economic consequences.** Students should explain what false positives, false negatives, precision, recall, F1-score, or related metrics mean in the specific business case. Evaluation should therefore become part of decision-making rather than only a technical reporting requirement.
- **Integrate AHP with predictive modelling and feature importance.** AHP criteria should not be selected independently from the analytical model. Students should explain how criteria are informed by model outputs, feature importance, business risks, costs, and implementation constraints. For example, if a model identifies lead quality, marketplace source, price, time-to-sale, or anomaly patterns as important predictors, students should explain how these variables influence the criteria used in AHP. This would help them avoid treating machine learning and multi-criteria decision-making as separate project sections.

These interventions suggest that industrial analytics projects should include explicit checkpoints for analytical-unit definition, decision-point identification, feature-availability review, validation-design justification, metric-to-risk interpretation, and model-to-decision integration. Such checkpoints can make methodological reasoning more visible and help students move from formal project completion toward coherent analytical decision support.

5 Conclusion

This paper analysed how students translate real industrial problems into analytical and decision-support tasks. Across the two industrial cases, students generally completed the required project components, including data preparation, modelling, evaluation, and AHP-based decision support. However, they were less consistent in defining the analytical unit, constructing a business-valid target variable, identifying feature availability at the decision point, justifying the validation design, and linking model results to operational or economic consequences. The main difficulty was therefore

not model training itself, but the transition from the business process to the analytical task and from model output to business decision. These findings indicate that industrial analytics projects should include explicit methodological checkpoints for analytical-unit definition, decision-point identification, feature availability, validation design, metric interpretation, and model-to-decision integration.

The study is limited to one interdisciplinary project, two industrial cases, and 14 student reports. The coding was descriptive and was not intended for statistical generalisation. Nevertheless, the analysis shows that student reports can provide useful evidence about how learners understand applied analytics as a methodological, technical, and decision-oriented process. Future work could extend the analysis to additional industrial cases, compare cohorts across academic years, and examine how targeted teaching interventions affect leakage awareness, validation quality, and decision-oriented interpretation. Further research could also examine team dynamics, collaboration challenges, and the implications of students' use of generative AI in interdisciplinary projects.

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