Model Quality and Student Satisfaction in BPMN Education: A Quasi-Experiment

Matheus Ribeiro Brant Nobre ¹⁰a, Jéssyka Vilela ¹⁰b and Lucas Migge de Barros ¹⁰c *Centro de Informática, Universidade Federal de Pernambuco (UFPE)*,

Av. Jornalista Aníbal Fernandes, s/n – Cidade Universitária, Recife-PE, Brazil {mrbn, jffv}@cin.ufpe.br, lucasmigge@gmail.com

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Modeling.

Abstract: Context: Teaching Business Process Management Notation (BPMN) is challenging due to its complexity.

Understanding how to improve BPMN education is crucial for technical accuracy and conceptual clarity. Objective: This study examines how individual and collaborative BPMN modeling impact model quality—correctness and completeness—as well as students' emotional experiences, including motivation, enjoyment, and relaxation. It also explores the influence of psychological profiles, based on the Keirsey typology, on these outcomes. Method: A quasi-experiment with 19 Information Systems students involved three BPMN modeling exercises of increasing complexity. Participants alternated between individual and collaborative modeling. Evaluations were based on BPMN quality criteria and emotional responses collected through Likert-scale questionnaires. Statistical analyses included Wilcoxon tests, Spearman correlations, and ANOVA. Results: There were no significant differences in correctness and completeness between approaches, though individual modeling slightly outperformed in technical metrics. Collaborative modeling increased enjoyment and relaxation without reducing technical performance, indicating a trade-off between emotional engagement and cognitive precision. Psychological profiles influenced outcomes, with Rationals achieving the highest quality models and Idealists the lowest. Conclusion: The study highlights the need to balance technical rigor and emotional engagement in BPMN education. Future research should explore long-term effects and collab-

1 INTRODUCTION

Business Process Management (BPM) education must extend beyond technical expertise, integrating analytical, modeling, and communication competencies essential for success in process-driven environments (Sarvepalli and Godin, 2017; Bandara and et al., 2010)(Nobre and Vilela, 2024).

orative tools to enhance BPMN training.

The Business Process Modeling Notation (BPMN) is widely used in industry to describe an organization's business processes, particularly valued for bridging communication between business and IT teams. However, mastering BPMN presents significant challenges for students due to its complex syntax and extensive range of elements, which require high cognitive effort to accurately model business processes.

^a https://orcid.org/0009-0000-0471-9280

b https://orcid.org/0000-0002-5541-5188

^c https://orcid.org/0009-0000-2323-5345

This diversity in pedagogical strategies underscores the importance of evaluating how these approaches influence critical metrics, such as BPMN model quality and student engagement. An underexplored area in BPM education is how individual versus collaborative modeling approaches influence model quality and students' learning experiences (Paschoal and et al., 2020). Besides the students' personality that influence the learning process, emotions play an important role in learning, influencing students' performance in challenging tasks.

Computing students often experience negative emotions, such as frustration and anxiety, during complex activities, but they also report positive emotions, such as satisfaction and pride, when overcoming obstacles (Atiq and Loui, 2022). This emotional dynamic underscores the need for instructional strategies that not only enhance technical skill but also address the emotional challenges inherent in BPMN modeling tasks.

We conducted a quasi-experiment examining the effects of individual and collaborative BPMN modeling on model quality and students' satisfaction. 19 Information Systems students alternated between modeling individually and in groups, enabling a comparative analysis of correctness, completeness, and self-reported emotions, including enjoyment, motivation, and relaxation.

The remaining of the paper is organized as follows. Section II explores background as well as related work. Section III outlines the quasi-experimental design. Section IV presents results. Section V contextualizes the findings within the existing literature, and Section VI offers pedagogical recommendations and directions for future research.

2 BACKGROUND

This section provides an overview of BPM, discusses how personality profiles and emotions influence the learning process, and reviews related work investigating the effectiveness of individual and group approaches in BPM education.

2.1 Keirsey Profile and Emotions

The Keirsey Profile, developed based on Jung's theory of personality types and the Myers-Briggs Type Indicator (MBTI), classifies individuals into four primary temperaments: Guardian, Artisan, Idealist, and Rational (Yilmaz and O'Connor, 2015).

These temperaments reflect behavioral predispositions that influence decisions and interactions in the work environment. When combined with PBL, Keirsey's analysis can reveal patterns of behavior and learning preferences (Arruda et al., 2019).

2.2 Related Work

Research on individual and collaborative modeling approaches in BPM education has yielded mixed results, reflecting the complexity of their impact.

An experimental study of (Paschoal and et al., 2020) compared BPMN modeling in individual and group contexts, finding no significant differences in correctness or completeness. However, collaborative activities enhanced engagement and participation, suggesting that teamwork's benefits extend beyond technical performance. In this context, the Social BPM Lab explored collaborative modeling using social software tools, emphasizing the development of communication and teamwork skills (Caporale and et al., 2013).

Although collaborative activities increased student engagement and knowledge exchange, they did not produce significantly better technical quality than individual modeling. This highlights the potential for cooperative activities to build interpersonal skills, even when their impact on technical outcomes is limited.

Despite these insights, notable gaps persist. We did not find studies that comprehensively examine the role of emotions in BPMN modeling or how emotional states relate to technical performance.

Moreover, the interplay between individual traits, such as personality profiles and collaborative dynamics, still needs to be explored. Addressing these gaps is relevant for advancing BPM education and ensuring that technical and interpersonal competencies are effectively developed.

3 RESEARCH METHOD

In this section, we describe the methodological approach employed in this study.

3.1 Participants

This paper focuses on an in-person BPM course, delivered in Portuguese, with 36 undergraduate students of the 4th semester from an Information Systems program who had little to no prior experience with BPM. The course spans 60 hours and incorporates a methodological approach that includes theoretical lectures, multiple modeling exercises, exams, and the execution of an interdisciplinary PBL project (dos Santos et al., 2023) in teams.

Six groups of six students were formed using the team formation method (TFM) (dos Santos, 2023), which integrates various aspects of students' profiles (Keirsey profiles, professional experience, gender and age, and work preferences). Previous studies have examined the impact of this method compared to self-selected teams on team performance (Vilela et al., 2024).

The first author were not involved in teaching or designing the studied course, and his only role was a researcher. The second author was the professor of the course.

3.2 Quasi-Experimental Design

The use of a quasi-experimental design in this study is justified by the organizational structure of the interdisciplinary PBL project [omitted due to blind review], which naturally groups students into predefined teams.

The primary goal of this study is to investigate the impact of individual and group modeling approaches on the quality of BPMN models and students' emotions during the learning process. To achieve this objective, we define three research questions:

RQ1: What emotions do students report when performing individual and group BPMN modeling?

RQ2: What are the differences in the technical quality of BPMN models (correctness and completeness) between individual and group modeling?

RQ3: Does personality profile, as defined by Keirsey's typology, influence the technical quality of models or students' emotions during modeling activities?

Aims to answer these questions, this quasiexperiment occurred in three main phases:

- 1. **Training and Familiarization.** Students participated in three classes about BPMN, covering theoretical foundations and practical modeling techniques using BPMN tools. A categorization questionnaire was administered to measure students' prior experience with process modeling, ensuring a baseline for future comparisons.
- 2. **Experimental Sessions.** This phase occurred in three stages:
 - **Stage 1.** All 36 participants individually modeled a process in BPMN.
 - **Stage 2.** The six groups were randomly assigned by drawing lots. Groups 2, 3, and 6 performed the modeling activity in groups, while Groups 1, 4, and 5 completed the exercise individually.
 - **Stage 3.** Students modeled another business process. Roles were reversed for the subsequent task, enabling cross-comparisons between individual and collaborative conditions.
- 3. Feedback and Data Collection. After each session, students completed self-report questionnaires to assess their emotional experiences (motivation, enjoyment, and relaxation) using a Likert scale represented by emojis. BPMN models were evaluated for correctness (accuracy in using BPMN elements and relationships) and completeness (including all relevant information for the modeled scenario) by assistant teachers using predefined criteria.

3.3 Hypotheses, Variables and Measurements

The formulation of research hypotheses, outlined in Table 1, was guided by the study's central questions and objectives research.

Table 1: Research Hypotheses.

ID	H ₀ (Null Hypothesis)	H ₁ (Alternative Hypothesis)					
H1	There is no significant differ-	There is significant difference					
	ence in correctness of BPMN	in correctness of BPMN mod-					
	models produced individually	els between individual and					
	and in groups.	group approaches.					
H2	There is no significant dif-	There is significant difference					
	ference in completeness of	in completeness of BPMN					
	BPMN models produced indi-	models between individual					
	vidually and in groups.	and group approaches.					
Н3	There is no significant dif-	There is significant differ-					
	ference in students' emotions	ence in students' emotions be-					
	(motivation, enjoyment, and	tween individual and group					
	relaxation) between individual	approaches.					
	and group modeling.						
H4	Keirsey profiles do not signif-	Keirsey profiles significantly					
	icantly influence correctness	influence correctness and					
	and completeness of BPMN	completeness of BPMN					
	models.	models.					

The variables were categorized to provide a structured understanding of the interactions between the treatments applied and the observed outcomes, as outlined in Table 2.

Table 2: Variables and Attributes.

Category	Description						
Independent	Tool used (Bizagi Modeler), model structures						
Variables (Pa-	(AS-IS and TO-BE), evaluation method.						
rameters)							
Independent	Modeling approach (individual or group),						
Variables (Fac-	Keirsey profile (Guardian, Artisan, Idealist,						
tors)	Rational).						
Dependent Vari-	Quality of BPMN models (Correctness and Com-						
ables	pleteness), Students' emotions (Motivation, En-						
	joyment, and Relaxation).						

Correctness (CR) and completeness (CM) were chosen as critical indicators of model quality, supported by prior BPMN evaluation studies (Paschoal and et al., 2020). CR was calculated using a weighted formula for error severity (light, medium, severe), offering a nuanced assessment of technical accuracy.

This weighted system provides a more detailed evaluation than binary correctness measures, capturing the practical significance of different error types for the model's usability. The formula for CR is:

$$CR = \frac{EC}{EC + (1 \times EI_{Light}) + (2 \times EI_{Medium}) + (3 \times EI_{Severe})}$$

The maximum correctness value (CR = 1) is achieved when all model elements are correct, with no errors. Conversely, CR = 0 reflects all elements being incorrect and classified as severe errors.

Completeness (CM) was calculated similarly, incorporating the presence of relevant information and the severity of omissions. This metric evaluates the quantity of information included and the impact of missing elements, emphasizing model comprehensiveness's practical significance in BPM contexts (Paschoal and et al., 2020).

By adhering to best practices in empirical research, these domain-specific metrics ensure reliable and objective technical assessments (Wohlin et al., 2012). The formula for CM is:

$$CM = \frac{IR}{IR + (1 \times FI_{Light}) + (2 \times FI_{Medium}) + (3 \times FI_{Severe})}$$

A completeness value of 1 indicates that all relevant information is included in the model, while 0 reflects the absence of all relevant information, with omissions classified as severe.

3.4 Data Collection and Analysis Procedures

Before the experimental activities began, in the interdisciplinary PBL project, participants completed a questionnaire with information such as group identifier, gender, age, years of work experience, and Keirsey profile.

The categorization questionnaire collected baseline data on participants' prior experience with modeling. This step was essential to control for confounding variables, ensuring that outcome differences could be attributed to the experimental treatments rather than external factors.

The BPMN modeling tasks were designed to replicate real-world scenarios involving AS-IS and TO-BE processes. The tasks ensured consistency across participants by using predefined case studies and a standardized tool (Bizagi Modeler) while allowing for variations in approach (individual or group).

Emotion questionnaires, as illustrated in Table 3, represented visually with emojis on a Likert scale, were employed to reduce subjectivity and ensure participant engagement.

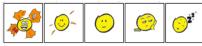
The data analysis followed a multi-step approach, leveraging a combination of statistical methods tailored to the research questions and the nature of the data. Each method was selected based on its suitability for addressing specific aspects of the experiment:

- Spearman's Correlation. This non-parametric test was employed to identify relationships between variables, such as the impact of prior experience on technical and emotional outcomes.
- 2. Wilcoxon Signed-Rank Test. The Wilcoxon test compared paired samples from individual and group modeling conditions. This test was selected for its ability to handle small sample sizes and non-normal data distributions, common in educational experiments.

Table 3: Questionnaire used to collect students' feedback regarding their emotions.

MOTIVATION

Regarding your MOTIVATION when learning about business process modeling. How did you feel before process modeling activity? (observe and select the image that best represents your MOTIVATION)



Totally motivated, Partially motivated, Neutral Partially, unmotivated Totally unmotivated.

FUN

Regarding FUN when learning about business process modeling. How did you feel during the process modeling activity? (observe and select the image that best represents your FUN)



Totally fun, Partially fun, Neutral, Partially boring, Totally boring.

RELAXATION

Regarding your feeling of RELAXATION during the modeling activity. How did you feel after the process modeling activity? (observe and select the image that best represents your RELAXATION)



Totally relaxing Partially relaxing Neutral, Partially stressful, Totally stressful.

3. **Repeated Measures ANOVA.** To evaluate variations across sessions and interactions between factors (e.g., Keirsey profile, modeling approach), a Repeated Measures ANOVA was conducted.

The study minimized the risks of type I and type II errors by triangulating findings across multiple statistical methods, ensuring robust and credible conclusions (Wohlin et al., 2012). These comprehensive procedures underscore the study's methodological rigor and contribution to advancing empirical research in BPM education.

3.5 Ethics and Transparency

Following best practices for empirical research (Wohlin et al., 2012; Kitchenham and et al., 2017), ethical procedures addressed concerns regarding voluntary participation, data confidentiality, and the separation of academic requirements from research components.

The Informed Consent Form clarified that participation in emotion assessments and feedback questionnaires was voluntary and anonymous, ensuring students could opt out without academic repercussions.

The BPMN modeling activities, mandatory for course evaluation, were explicitly separated from optional research elements, preventing coercion and up-

holding ethical standards.

Transparency was emphasized, with participants informed about how their data would contribute to pedagogical improvements and academic literature. The consent form included detailed explanations of how the data would be aggregated, analyzed, and reported, ensuring that no personal identifiers would be linked to the results.

3.6 Threats to Validity

Following the guides proposed by (Wohlin et al., 2012), we addressed four key validity concerns. *Internal Validity*: Participants' prior BPMN experience potentially threatened internal validity by influencing model quality. To mitigate this, a categorization questionnaire assessed participants' backgrounds, and standardized training sessions were conducted to equalize BPMN competencies.

Another factor is the mix of parametric (ANOVA) and non-parametric (Wilcoxon, Spearman) tests. We applied ANOVA to compare personality profiles because the data approximated normality, while using Wilcoxon and Spearman for paired and ordinal data. *External Validity*: The limited sample size (19 participants after data processing) and the academic context restricted the generalizability of findings to broader professional or cross-institutional settings.

Moreover, the controlled academic environment may only partially capture the complexities of professional BPMN tasks, such as time constraints and organizational challenges. Interdisciplinary PBL projects were employed to simulate real-world scenarios, but caution is needed when extrapolating findings to industrial contexts.

Construct Validity:

Validated criteria from BPMN literature, reviewed by domain experts, were used to define correctness and completeness. The emoji-based Likert scale enhanced emotional engagement and clarity, but integrating additional validated emotion scales could provide more excellent reliability and nuance in future research.

Ecological Validity: While the academic setting offered controlled conditions for studying BPMN modeling, it differed from professional contexts involving higher stakes, collaborative dynamics, and larger datasets. The interdisciplinary PBL framework partially addressed this by simulating real-world challenges, but further studies in industrial environments would strengthen ecological validity.

4 RESULTS

The dataset was derived from 33, 30, and 19 students for Exercises 1, 2, and 3, respectively. After excluding incomplete data, 19 participants who completed all three questionnaires were retained to ensure reliable analysis.

4.1 RQ1: What Emotions Do Students Report when Performing Individual and Group BPMN Modeling?

Participants' emotional responses were evaluated using Wilcoxon tests and Spearman correlations. As shown in Table 4, the Wilcoxon test revealed no statistically significant differences between individual and group modeling for motivation (p=1.000), enjoyment (p=1.000), and relaxation (p=0.824).

These results suggest that the modeling activity format did not substantially influence the reported emotions, leading to the retention of the null hypothesis (H_3) .

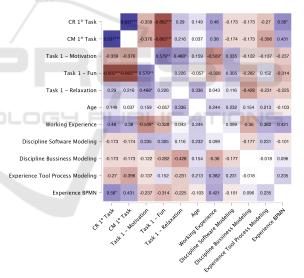


Figure 1: Spearman Correlation - Task 1.

The Spearman correlations analysis for the first BPMN modeling, visualized in Figure 1, highlighted significant relationships between emotional dimensions. Motivation strongly correlated with enjoyment ($\rho = 0.579, p < 0.01$) and relaxation ($\rho = 0.468, p < 0.05$), indicating an intrinsic link between these positive emotional states.

Additionally, a strong negative correlation between correctness and enjoyment ($\rho = -0.802, p < 0.001$) emerged, suggesting an inverse relationship where higher enjoyment corresponded to lower correctness scores. This points to a potential tension be-

				-					
Measure 1		Measure 2	Test	Statistic	z	df	p	Effect Size	SE Effect Size
Individual Task - Correctness	-	Group Task - Correctness	Student	0.892		12	0.390	0.248	0.434
			Wilcoxon	47.000	0.628		0.556	0.205	0.316
Individual Task - Completeness	-	Group Task - Completeness	Student	1.039		12	0.319	0.288	0.424
			Wilcoxon	58.000	0.874		0.414	0.275	0.305
Individual Task - Fun	-	Group Task - Fun	Student	-0.195		18	0.848	-0.045	0.241
			Wilcoxon	52.000	-0.031		1.000	-0.010	0.294
Individual Task - Motivation	-	Group Task - Motivation	Student	0.000		18	1.000	0.000	0.179
			Wilcoxon	22.500	0.000		1.000	0.000	0.358
Individual Task - Relaxation	-	Group Task - Relaxation	Student	0.271		18	0.790	0.062	0.197
			Wilcoxon	30.000	0.255		0.824	0.091	0.342

Table 4: Paired Samples T-Test.

tween emotional engagement and technical precision.

Participants with prior modeling experience reported greater enjoyment, underscoring the role of familiarity and competence in shaping emotional responses. These findings emphasize the need for future studies to consider how prior knowledge and task complexity interact to shape emotional and technical outcomes in BPM learning environments.

4.2 RQ2: What Are the Differences in the Technical Quality of BPMN Models (Correctness and Completeness) Between Individual and Group Modeling?

To examine differences in technical quality, we analyzed correctness (CR) and completeness (CM) using Wilcoxon tests and Spearman correlations.

As shown in Table 4, the Wilcoxon test found no significant differences between individual and group modeling in correctness (p = 0.628) or completeness (p = 0.874).

This supports the null hypotheses (H_1 and H_2), indicating that the modeling format did not significantly impact technical quality. Notably, both conditions yielded high average scores in CR and CM, reflecting students' solid grasp of BPMN concepts.

The individual modeling correlations, depicted in Figure 2, showed a strong positive association between correctness and completeness ($\rho = 0.957, p < 0.001$). This relationship underscores the interconnectedness of technical precision and conceptual understanding in BPMN modeling.

Similarly, Figure 3 highlights how prior work experience positively influenced completeness ($\rho = 0.590, p < 0.05$) in group tasks, suggesting that real-world exposure plays a crucial role in enhancing model quality.

These results align with prior studies suggesting that while collaboration fosters interpersonal skills and engagement, its impact on technical quality may

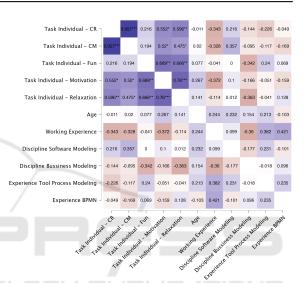


Figure 2: Spearman Correlation - Individual Task.

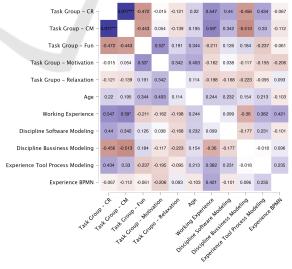


Figure 3: Spearman Correlation - Group Task.

depend on participants' experience levels and task complexity.

4.3 RQ3: Does Personality Profile, as Defined by Keirsey's Typology, Influence the Technical Quality of Models or Students' Emotions During Modeling Activities?

To assess the impact of Keirsey profiles, ANOVA analyzed differences across personality types, and Wilcoxon tests evaluated emotional variations.

The ANOVA results, illustrated in Figures 4 and 5, demonstrated significant differences in correctness (F = 6.761, p < 0.01) and completeness (F = 4.153, p = 0.038) across profiles.

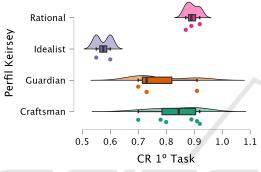


Figure 4: ANOVA - Keirsey CR.

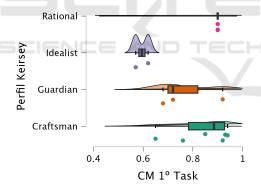


Figure 5: ANOVA - Keirsey CM.

Rationals achieved the highest CR (M = 0.893) and CM (M = 0.900), while Idealists scored the lowest (CR: M = 0.575, CM: M = 0.595). These findings reject the null hypothesis (H_4), confirming that personality traits significantly influence technical outcomes.

Conversely, Wilcoxon tests revealed no significant differences in emotional responses between profiles (p>0.05). This indicates that while personality influences technical performance, emotional experiences during modeling activities remained consistent across types.

These insights suggest that personality traits, particularly those of Rationals, can be strategically leveraged to enhance team performance and task outcomes. Idealists, however, may benefit from targeted support and technical reinforcement.

Future research could explore how adaptive teaching methods cater to diverse personality profiles, optimizing technical precision and emotional engagement.

5 DISCUSSION

A notable contribution of our study is the examination of emotions alongside technical indicators. We detected a negative correlation between enjoyment and correctness, suggesting that greater enjoyment might correspond to lower perceived cognitive effort, aligning with the idea that high "fun" can sometimes detract from meticulous task execution (Van Merrienboer and Ayres, 2005).

Further, incorporating Keirsey personality profiles showed that Rationals performed best in terms of correctness and completeness, whereas Idealists lagged. This finding reinforces the idea that personal traits and learning preferences can influence modeling outcomes, offering actionable insight for educators who might tailor support or team composition accordingly.

Taken together, our results support earlier arguments that collaboration boosts positive emotions and interpersonal engagement but does not inherently increase technical quality in BPMN modeling. They also expand the conversation by linking personality factors to outcomes.

Despite the limited sample, this research extends BPM education literature by weaving together technical metrics, emotional measures, and personality profiles within a single quasi-experimental study. Such an approach underlines the complexity of BPMN instruction, where cognition, affect, and interpersonal dynamics all converge.

6 CONCLUSIONS AND FUTURE WORK

This study provides new insights into the intersection of technical performance, emotional engagement, and individual characteristics in BPM education. Our findings demonstrate no statistically significant differences in the correctness and completeness of BPMN models between individual and collaborative modeling approaches.

This suggests that while collaborative activities may enhance interpersonal dynamics and engagement, they do not inherently improve technical accuracy or comprehensiveness. Furthermore, the strong correlations between emotional states—such as motivation and enjoyment—and technical performance highlight the multifaceted nature of the learning experience.

By integrating personality profiles and prior experience as variables, our study goes beyond traditional analyses to emphasize the individualized factors influencing BPM learning. Identifying personality traits, such as the Rational profile's tendency for higher technical quality, offers valuable insights for educators seeking to design tailored learning strategies.

Longitudinal studies examining how personalized interventions based on personality profiles affect long-term learning outcomes are recommended. Comparative analyses across different institutions and cultural contexts could offer a more comprehensive understanding of BPM education's global applicability.

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