



AI-ASSISTED INFOGRAPHIC DESIGN FOR DATA STORYTELLING: EFFECTS ON QUALITY, EFFICIENCY, AND CREATIVITY IN EDUCATION

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ABSTRACT

Aim/Purpose	This study investigates whether an AI-assisted infographic generation tool can enhance infographic quality, support creativity, and improve efficiency in educational settings compared to conventional design tools.
Background	Infographics are a powerful medium for data storytelling, but require significant design expertise and time, often creating barriers for students. This paper evaluates an AI-based infographic generation tool that automates layout and visual design, examining its effects on output quality, task efficiency, and perceived support for creativity in a university Data Visualization course.
Methodology	Two controlled experiments were conducted with undergraduate and postgraduate students enrolled in a Data Visualization module. In each experiment, participants were divided into control (conventional tool) and experimental (AI tool) groups and completed a data storytelling task by creating an infographic. Outputs were evaluated using a structured rubric, while student perceptions were captured through a usability questionnaire and the Creativity Support Index (CSI). Independent samples t-tests and ANOVA were used for analysis.
Contribution	This paper contributes empirical evidence to the emerging discourse on AI-assisted creativity in education. It provides a comparative evaluation of AI-generated and template-based infographics across objective quality measures,

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	time efficiency, perceived usability, and support for creativity, highlighting both the benefits and trade-offs of automation in creative learning tasks.
Findings	Infographics created using the AI tool achieved substantially higher overall quality scores than those created with the conventional design tool, improving rubric scores by 35% among undergraduates (86.8 vs. 64.5) and 26% among postgraduates (86.9 vs. 69.1). The largest gains were observed in layout, visual elements, and data visualization quality. The AI tool also reduced task completion time by 30% for undergraduates (from 113.5 to 79.1 minutes), and by 38% for postgraduates (from 86.0 to 53.6 minutes). Students in the control groups reported greater perceived usability and a greater sense of control over layout and design decisions. Postgraduate students rated the AI tool more positively for its creativity support than undergraduates did. The results indicate a trade-off between efficiency and user agency when integrating AI into creative design tasks.
Recommendations for Practitioners	Educators integrating AI tools into design or visualization courses should balance automation with opportunities for learner control and customization. Providing scaffolding and training may improve perceived usability and support smoother adoption, especially among less experienced students.
Recommendations for Researchers	Future research should further explore learner agency, long-term skill development, and the interaction between prior experience and AI tool acceptance. Comparative studies across disciplines and task types can deepen understanding of AI's role in creative education.
Impact on Society	By demonstrating how AI can enhance both efficiency and output quality in visual communication tasks, this study informs the responsible integration of generative tools in education. It highlights the importance of designing AI systems that augment, rather than replace, human creativity and decision-making.
Future Research	Future studies should examine the longitudinal effects of AI-assisted design on students' independent creative skills, investigate adaptive AI systems that allow adjustable levels of automation, and explore collaborative AI-supported infographic design environments.
Keywords	artificial intelligence, data storytelling, automated visualization, education technology

INTRODUCTION

In today's data-driven world, the exponential growth of information across diverse fields has created both opportunities and challenges for effective communication. As data grows larger and more complex, there is an increasing need for tools that present insights in accessible, engaging, and memorable forms. Infographics have emerged as a widely adopted medium for this purpose, combining graphical elements, text, charts, and maps to transform complex data into coherent visual narratives (Naparin & Binti Saad, 2017). Their ability to integrate storytelling with visual design makes them not only powerful for professional communication but also valuable as educational tools (Alyahya, 2019; Damyanov & Tsankov, 2018). In learning environments, infographics help simplify complex information, allowing students to comprehend abstract concepts and retain information.

Beyond their role in simplifying information, infographics serve as powerful tools for data storytelling or narrative visualization, in which information is structured into a meaningful narrative that highlights trends, comparisons, and insights (Kosara & Mackinlay, 2013; Z. Wang et al., 2019). In business analytics education, this storytelling ability is particularly important, as students are expected to move beyond

technical analysis and develop the skills to communicate data insights effectively to diverse stakeholders (Herschel & Clements, 2017).

Despite their effectiveness, creating high-quality infographics remains a cognitively demanding task that requires both graphic design expertise and domain knowledge. Although online platforms such as Canva, Mind the Graph, and Piktochart make it convenient to create infographics by simplifying the process, they still require a certain level of design skills. Many users may struggle with fundamental design principles such as color theory, layout composition, and typography (W. Zhu et al., 2024).

The automation of visualization generation is an emerging field aimed at easing the creation of visualizations, especially for non-expert users (Wu et al., 2022). Automatic visualization tools try to lower the barrier to entry by generating visualizations automatically, rather than creating them manually (S. Zhu et al., 2020). While such tools have been shown to be effective in generating specific kinds of charts and infographics (Cui et al., 2020; Qian et al., 2021; Zhu-Tian et al., 2020), there is limited research on their support for higher-level tasks such as narrative construction, creative expression, and learning. In the context of business analytics education, where students must not only produce accurate visuals but also create compelling data stories, this gap becomes especially pronounced. Transforming complex data into data stories that resonate with stakeholders and enable them to make informed decisions is an important skill the students must learn. As such, integrating automated tools offers an opportunity to enhance the effectiveness of business analytics education.

However, while these systems may improve efficiency and reduce the cognitive effort required to create visualizations, concerns remain regarding their impact on quality, efficiency, student agency, creative decision-making, and learning processes. Educational research has highlighted the importance of maintaining learner autonomy and active engagement when interacting with AI systems, suggesting that excessive reliance on automation may limit opportunities for creativity, reflection, and skill development (Agarwal & Sivaraman, 2025; Alm, 2024; Gupta et al., 2025). Consequently, it remains unclear whether AI-assisted infographic tools support learning by enabling students to focus on higher-level storytelling tasks or whether they reduce meaningful involvement in the design process.

This study addresses this gap by developing an automated infographic generation tool and evaluating it in the context of business analytics education. Specifically, the study investigates whether such a tool can improve the quality and efficiency of infographic creation and examines students' perceptions of usability, support for creativity, and control over the design process. To evaluate its educational impact, we conducted two controlled experiments with undergraduate and postgraduate students enrolled in a Data Visualization module as part of their Business Analytics programs. Students were divided into experimental and control groups, with the former using the AI tool and the latter employing the conventional design platform Canva.

Based on these experiments, the study addresses the following research questions:

- To what extent does the AI-based tool improve the quality of infographics compared to traditional tools?
- Does the AI-based tool reduce the time required to create infographics?
- How do students perceive the usability and creativity support of the AI-based tool relative to conventional tools?
- Are there differences in the adoption and perception of the tool between undergraduate and postgraduate students?

LITERATURE REVIEW

The literature review is organized as follows. The first subsection reviews the literature on data storytelling, which focuses on integrating data, visuals, and narratives to communicate insights from data analyses effectively. The next subsections explore infographics as a key medium for visual storytelling and the principles of effective infographic design. Then the next subsection examines research on the automation of visualization generation, an emerging field that seeks to simplify the process of creating data visualizations. The final subsection looks at the use of generative artificial intelligence in education, focusing on its role in supporting learning and creativity, as well as its impact on learner agency and educational outcomes.

DATA STORYTELLING

Data storytelling is the process of translating data analyses into explanations by combining narratives, data, and visuals to produce data stories. It can help an audience that might not have the necessary skills to interpret the raw data understand the key points more effectively and efficiently (Shao et al., 2024). It improves effectiveness in understanding insights compared to conventional visualizations.

Data storytelling is a crucial part of a comprehensive business analytics/data science education, alongside basic analytical skills (Chen et al., 2024). Integrating data storytelling into analytics education not only enhances students' ability to present insights but also fosters cross-disciplinary communication, preparing them for the demands of a data-driven workforce (Chen et al., 2023). Despite its importance, there is a lack of a thorough understanding of the concepts and methods of building data storytelling among students (Chen et al., 2024).

Crafting effective data stories requires following certain guidelines to take the audience through a journey of insight. Deshpande introduces seven such design principles covering appropriate visuals, maximizing the data-ink ratio, whitespace, and actionable narratives (Deshpande, 2023). dos Santos Lonsdale (2022) provides a more comprehensive set of guidelines for information visualization design and is further discussed under the next section.

INFOGRAPHICS

Infographics are visual representations of information, data, or knowledge that are designed to present complex information more clearly than text alone. By combining words, numbers, symbols, colors, and pictures, infographics communicate a key message to readers by telling a story (Niebaum et al., 2015).

Infographics serve as powerful tools for communication and education across various fields, effectively blending visual and textual elements to enhance understanding. They are especially helpful in educational contexts because of their capacity to explain difficult ideas, such as those in mathematics (Baglama et al., 2020). Infographics provide students with a more engaging and effective way to learn, and it has been shown (Bicen & Beheshti, 2017) that students prefer visual materials and find infographics helpful for understanding and retaining information.

Infographics are a primary medium for data storytelling, as they can transform diverse data into visually engaging narratives. Research indicates that infographics are particularly effective in conveying economic and financial information (Viytovych, 2024) and in explaining complex phenomena such as urban change (De Simone et al., 2014). An emerging practice known as data journalism uses infographics as a communication tool to bridge the gap between complex data and the general public (Fu & Stasko, 2024). Infographics also enhance decision-making across various domains, including health promotion (Hätönen & Tolonen, 2021), by simplifying complex information, making it more understandable and accessible. By focusing attention on important information from the bottom up and reducing cognitive load through efficient visual encoding techniques, visualizations can facilitate the interpretation and evaluation of complex data, thereby enhancing accuracy and efficiency in decision-making (Padilla et al., 2018).

PRINCIPLES OF EFFECTIVE INFOGRAPHICS

An infographic is considered ‘good’ primarily for its function, with visual appeal secondary. dos Santos Lonsdale (2022) states that an infographic’s aesthetic attractiveness cannot make up for weak content and design. Since the main objective of infographic design is to communicate information efficiently, adhering to specific guidelines is essential to reaching that objective. dos Santos Lonsdale (2022) provides eleven general guidelines for infographic design, focusing on how users read infographics. The guidelines include focus, key message, visuals for comprehension, appropriate text, deliberate color, effective elements, data visualization, user-friendly charts, accurate data, balance, and user needs.

Multiple researchers highlight clarity of the message as a key aspect of infographic design (Midway, 2020; Traboco et al., 2022). Infographics ought to have a well-defined objective so that the intended audience can understand the core message (Traboco et al., 2022). Since effective information communication is the main objective of any visualization, a clear message helps focus the viewer’s attention on the key elements and information presented, ensuring that the intended information is communicated without ambiguity (Midway, 2020).

The aesthetic appeal of an infographic, particularly its color and visual complexity, significantly contributes to the initial impression it makes on the audience (Harrison et al., 2015), and aesthetic qualities in visualizations have been shown to positively impact outcomes such as engagement and memorability (Borkin et al., 2013). Color plays a crucial role in the aesthetics of effective infographics by influencing emotions and perceptions (Midway, 2020; Piechnik-Czyż & Gruszczyńska, 2024). Properly selected colors can highlight important information, engage readers, and enhance understanding, making the overall design more appealing and effective in conveying messages.

AUTOMATION OF VISUALIZATION GENERATION

An emerging field, “automation of visualization generation,” aims to make creating visualizations easier, particularly for non-expert users (Wu et al., 2022). It tackles the difficulties of conventional visualization production, which can be challenging and mentally demanding, even for professionals. Automatic visualization tools aim to lower the barrier to entry by generating visualizations for users to search and choose from, rather than requiring them to specify them manually (S. Zhu et al., 2020).

Infographics Wizard (Tyagi et al., 2022), an interactive tool for automating and exploring infographic design, leverages the concepts of Visual Information Flow (VIF) and Visual Groups (VG) to provide flexible design options. DataShot (Y. Wang et al., 2020) is an automated system designed to generate informative and visually appealing fact sheets directly from tabular data. The system leverages qualitative analysis of award-winning infographics to inform its design choices, automatically selecting visualizations and organizing data points into topics. Another system that automatically creates infographics from basic statements about proportions is called Text-to-Viz (Cui et al., 2020). The authors describe a method that uses pre-made templates to render proportion-related information.

Research (Li et al., 2024) conducted on existing automated visualization and data storytelling tools identifies four roles that humans and AI play in the storytelling workflow: Creator, Assistant, Optimizer, and Reviewer. The Creator role does most of the work and takes a high level of control in storytelling. As an example, DataShot (Y. Wang et al., 2020) serves as the creator role, doing most of the visualization work. The Assistant role works with creators, helping them simplify tasks such as recommending color palettes, as in Infocolorizer (Yuan et al., 2022). Optimizers focus on improving existing data stories, while reviewers assess and provide feedback on them. Further, they propose a four-stage framework (analysis, planning, implementation, and communication) in which these roles are played out.

AI IN EDUCATION

Generative Artificial Intelligence (GenAI) is increasingly transforming educational environments by enhancing teaching, learning, and content creation processes. Recent studies suggest that GenAI has the potential to personalize learning experiences, improve student engagement, and support educators in

delivering more effective instruction. By dynamically adapting educational content to individual learner needs, GenAI enables more tailored learning pathways that can accommodate diverse learning styles and abilities (Agarwal & Sivaraman, 2025; Kovari & Katona, 2024).

A major advantage of GenAI in education is its ability to support personalized learning and pedagogical practices. AI-powered systems can analyze learner behavior, adapt instructional materials, and provide individualized recommendations and feedback (McDonald et al., 2025). Furthermore, GenAI can assist educators in creating learning resources, including summaries, assessments, and instructional content, thereby reducing administrative workload and allowing educators to focus more on teaching and student support (Gupta et al., 2025; McDonald et al., 2025).

Beyond personalization, GenAI has been shown to enhance student engagement and learning efficiency. Students frequently utilize tools such as ChatGPT to clarify concepts, receive immediate feedback, and support academic writing activities (Almassaad et al., 2024). These capabilities can promote more accessible and responsive learning experiences while fostering innovative approaches to knowledge acquisition and problem-solving (Gaftandzhieva, 2025). Additionally, GenAI tools can facilitate intellectual tasks and encourage experimentation with new learning strategies, contributing to improved educational outcomes.

Despite these benefits, the adoption of GenAI in education is accompanied by several challenges. Research indicates that user receptiveness to AI-powered educational tools is mixed, with some learners and educators expressing concerns about their reliability and appropriate use (Kovari & Katona, 2024). Ethical issues, particularly those related to academic integrity, plagiarism, and overreliance on AI-generated content, remain significant concerns (Agarwal & Sivaraman, 2025; Almassaad et al., 2024). There is also concern that excessive reliance on AI systems may diminish critical thinking, learner autonomy, and meaningful engagement in the learning process (Agarwal & Sivaraman, 2025; Gupta et al., 2025).

In AI-supported learning environments, student agency has emerged as a critical factor influencing educational outcomes. Alm (2024) observed that effective use of AI involves a form of shared agency, where learners engage productively with AI tools while maintaining critical awareness and decision-making responsibility. Similarly, Yang et al. (2024) identified learner agency as central to students' interactions with GenAI, highlighting diverse approaches ranging from receptive and resourceful engagement to resistive and reflective use. These findings suggest that educational benefits are maximized when learners remain active participants in the learning process rather than passive consumers of AI-generated outputs.

To address these concerns, scholars emphasize the importance of establishing institutional policies, implementation strategies, and quality assessment frameworks for AI-generated educational content (Gaftandzhieva, 2025). Clear guidelines governing the responsible use of GenAI, combined with appropriate human oversight, are considered essential for balancing the technology's educational benefits with the need to maintain academic standards and ethical practices (Almassaad et al., 2024). Recent research has further highlighted the need to understand and measure learner agency in AI-supported educational contexts. Xia et al. (2025) conceptualized student learning agency in generative AI environments. They identified overreliance on AI technologies as a potential threat to autonomous learning and proposed a validated scale to assess learner agency in such settings. Collectively, these studies indicate that successful integration of GenAI in education requires not only technological effectiveness but also the preservation and enhancement of student agency, autonomy, and critical engagement. Overall, the literature suggests that Generative AI offers substantial opportunities to enhance educational effectiveness through personalized learning, content generation, and increased student engagement. However, realizing these benefits requires careful implementation, robust governance mechanisms, and educational practices that empower learners to maintain control over their learning processes while leveraging AI as a supportive partner.

While previous studies have demonstrated the importance of storytelling, visualization, and the growing role of automation in easing visualization design, much of the research remains focused on technical

contexts. Though their use in educational settings has received little attention, automated visualization and data storytelling tools have shown promise in reducing cognitive effort and improving communication. In particular, little is known about how such tools can support students in developing data storytelling skills, balance creativity with usability, or influence learning outcomes in structured academic environments. Furthermore, emerging research emphasizes the importance of maintaining learner agency and autonomy when interacting with AI systems. Yet empirical evidence on these factors in visualization and infographic design remains limited. This study addresses these gaps by investigating the effectiveness of an AI-powered infographic generation tool in business analytics education, examining not only the quality and efficiency of infographic creation but also students' perceptions of support for creativity, usability, and agency during the design process.

METHODOLOGY

The methodological approach of this study was structured in two main phases: tool development and experimental evaluation (Figure 1). First, a web-based infographic generation tool named *Narrativ* was developed to address the technical and creative challenges students often face when designing infographics. Once the tool was fully developed and tested, a series of controlled classroom experiments was conducted to evaluate its educational effectiveness. The experiments examined how *Narrativ* influenced infographic quality, task completion time, and students' perceptions of usability and support for creativity compared to the conventional design tool Canva.

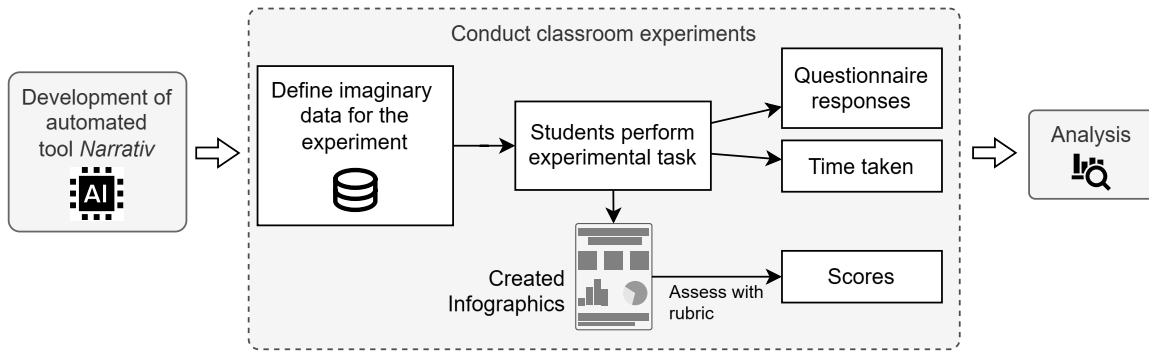


Figure 1. Overview of the research methodology

The following subsections describe the tool development, experimental design, study procedure, and data analysis in detail.

TOOL DEVELOPMENT

To facilitate the experimental study, we developed a web-based infographic generation tool named *Narrativ*. The tool was designed to reduce the technical barriers of infographic creation while still providing students with opportunities for creative control. Upon launching the application, users are greeted with an input interface (Figure 2) that accepts a textual description in a markdown-like syntax. A help panel is provided to guide users in formatting their descriptions to generate different types of visual outputs. For example, the following input automatically produces an infographic with a title and a bar chart.

```

# Company Overview
## Monthly Sales [Bar chart]
- January: 100
- February: 120
- March: 110

```

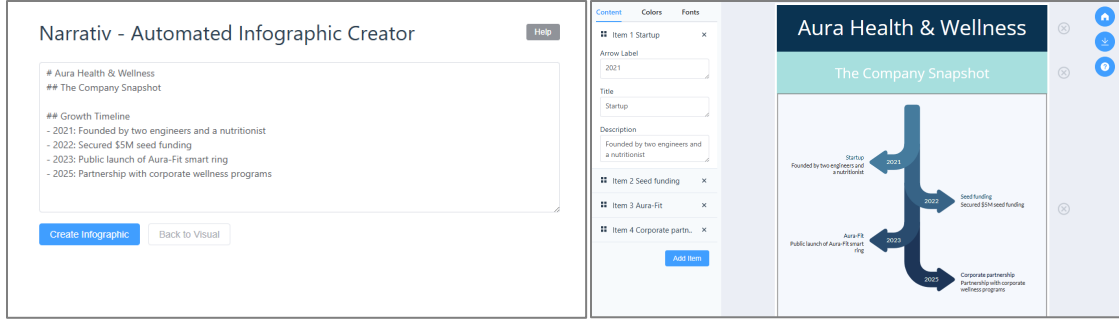


Figure 2. Screenshots of the automated infographic generation tool

The underlying architecture leverages the GPT-4.1-nano model in a zero-shot setting to parse the user’s textual input into a structured representation aligned with a predefined schema of supported infographic elements. These include text blocks, charts, lists, timelines, cycles, and other graphical elements. The structured representation is then rendered into scalable vector graphics (SVG).

The design of *Narrativ* is centered on the concept of Visual Groups (VGs) (Lu et al., 2020), each encapsulating a distinct unit of information. At the atomic level, a VG typically combines symbolic graphical depictions (such as shapes, icons, or images) with textual details to convey meaning. These VGs are then arranged according to a Visual Information Flow (VIF) (Lu et al., 2020), which defines the logical sequencing of content. Depending on the narrative, VIFs may take the form of lists that present items in an ordered structure, process diagrams that depict step-by-step workflows, cycles that represent repeating patterns, or timelines that display events in chronological order. To support these structures, the tool incorporates a set of inbuilt graphical templates for both VGs and VIFs, which are automatically selected based on the type of content generated, thereby ensuring both consistency and contextual relevance in the resulting infographics.

Once the initial infographic is generated, users are taken to an editor view (Figure 2). Here, *Narrativ* automatically suggests a vertically aligned linear layout with appropriate color palettes, icons, and fonts. Users retain the flexibility to refine their work through a range of manual editing capabilities. Individual visual elements can be selected and modified, allowing users to edit text, replace icons from an integrated icon library, and adjust the underlying data displayed within visual components. For example, users can add, edit, or delete items within lists, process diagrams, timelines, and charts, enabling the infographic to evolve beyond the system’s initial suggestion. Visual styling can also be customized through a curated collection of color palettes and font families, allowing users to adapt the infographic to different themes and preferences while maintaining visual consistency.

However, users cannot request the AI to iteratively revise or refine an existing infographic. Instead, if they are dissatisfied with the generated structure or overall design, they must return to the initial interface and regenerate the infographic from the original text description. Since the generation process is non-deterministic, repeated generations from the same description may produce substantially different infographic layouts and visual compositions. This design choice was intended to provide users with multiple design options while keeping the editing interface focused on content and stylistic customization rather than AI-assisted layout modifications.

According to the human-AI collaboration framework proposed by Li et al. (2024), *Narrativ* functions primarily during the planning and implementation stages, while the analysis and communication stages fall outside its scope (Figure 3). In the planning stage, the human user serves as the creator, defining the facts and their order. In contrast, *Narrativ* serves as the optimizer, adjusting the content to ensure a logical flow for the infographic. In the implementation stage, *Narrativ* assumes the creator role, controlling the layout and visual elements. Still, the user can play the role of the optimizer by customizing the text, colors, and other styles.

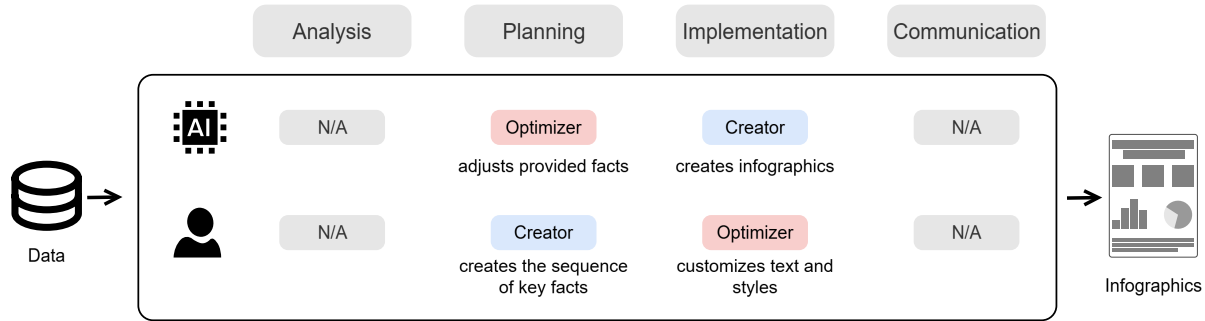


Figure 3. Roles of human and AI collaborators for Narrativ

The tool currently supports only vertical linear layouts, which simplifies cognitive load for novice users and ensures consistency across outputs. Completed infographics can be exported as image files for inclusion in reports, presentations, or assignments. This development approach enabled Narrativ to serve as both a productivity tool and an experimental platform for evaluating the impact of automated design support in business analytics education.

EXPERIMENTAL DESIGN

Participants

The evaluation of *Narrativ* was conducted through two controlled classroom experiments with undergraduate and postgraduate student groups, enrolled in business analytics degree programs.

The undergraduate experiment involved 49 students (24 male, 25 female), aged between 21 and 23 years ($M = 21.9$). All participants reported prior familiarity with Power BI, and 44 of them were also familiar with Canva as a design tool. Regarding self-assessed visualization skills, 28 students identified themselves as intermediate, while the remaining participants identified themselves as beginners.

The postgraduate experiment included 50 students (25 male, 25 female), aged between 24 and 43 years ($M = 30.6$). Similar to the undergraduate group, all participants reported familiarity with Power BI, while 36 indicated prior experience with Canva. In terms of visualization expertise, 18 students identified themselves as beginners, 30 as intermediate, and 2 as advanced.

Study Procedure

Participants were randomly assigned to either a control group, which used the tool Canva for infographic creation, or an experimental group, which used *Narrativ*. Canva was selected as the control condition because it is a free, user-friendly design platform familiar to many students. Its widespread adoption in educational settings made it an appropriate baseline for comparing *Narrativ*. To ensure consistency across participants and to represent typical student usage, all members of the control group used the free version of Canva.

The experimental task was standardized across groups. Students were provided with a description of an imaginary company named “Aura Health & Wellness,” including its background, milestones, sales, and user engagement data. Their task was to: (1) understand and extract key insights from the given information; (2) plan a narrative to communicate; and (3) create an infographic that effectively conveyed the company’s story. This activity was designed with three key expected learning outcomes (LOs):

- LO1:** Students will be able to identify key information and translate it into a coherent narrative.
- LO2:** Students will be able to design infographics that apply principles of layout, typography, and color to enhance communication.
- LO3:** Students will be able to select suitable visual forms to represent different data types and relationships.

The study sessions started with a 10-minute tutorial demonstrating the tools. Upon completion, participants also responded to a questionnaire to capture their previous experience with visualization design, and other aspects. It also included the standard set of questions of the Creativity Support Index (CSI) (Cherry & Latulipe, 2014), a well-established instrument for measuring how well a tool supports users' creativity, expressiveness, engagement, and satisfaction. A structured rubric was developed to assess the quality of the infographics created by the participants. This rubric was based on dos Santos Lonsdale's eleven general guidelines for infographic design (dos Santos Lonsdale, 2022; Siricharoen & Siricharoen, 2015), and was simplified to cover seven key criteria: clarity of purpose, information accuracy, layout balance, use of visual elements, color selection, appropriateness of data visualizations, and overall engagement. Each criterion was scored across four performance levels (excellent, good, fair, poor), enabling a detailed assessment of both strengths and weaknesses in student outputs. Table 1 maps the learning outcomes expected from the activity to the rubric criteria.

Table 1. Mapping of learning outcomes to rubric criteria

Criterion	LO1	LO2	LO3
1. Clear purpose and relevance to target audience	✓		
2. Information accuracy and reliability	✓		
3. Layout, balance, and clutter		✓	
4. Visual elements for comprehension and engagement			✓
5. Color selection		✓	
6. Appropriate data visualizations			✓
7. Engagement and first impression	✓	✓	✓

A single external expert with experience in infographic design and visual communication performed the rubric-based assessment. Before the evaluation, the expert was briefed on the infographic design task, including the scenario provided to participants, the activity's intended learning outcomes, and the assessment rubric and its associated scoring criteria. A blind evaluation procedure was employed, whereby the evaluator was not informed of the tool used to create each infographic. Figure 4 presents sample infographics produced by participants in the study. This approach helped minimize evaluator bias and ensured that scores were based solely on the quality of the submitted artifacts. Because only one expert evaluator was involved, inter-rater reliability was not assessed.

This dual evaluation approach (combining rubric-based outcome assessment with self-reported perceptions of creativity support) enabled a comprehensive understanding of both the effectiveness of the generated infographics and the user experience of working with *Narratin*.

This study was conducted in accordance with the research ethics guidelines and the university's institutional requirements. As the activity formed part of a routine classroom exercise conducted within the normal academic context and involved only low-risk educational evaluation and feedback, it fell within the category of activities exempt from formal ethical review under the applicable institutional requirements. Although the questionnaire collected students' index numbers, these were used solely to verify the response cohort and group and were removed from the dataset before analysis. The questionnaire responses and infographics produced by the participants were subsequently anonymized to maintain confidentiality and protect the integrity of the research data. Participation was voluntary, and informed consent was obtained from all participants before their participation.

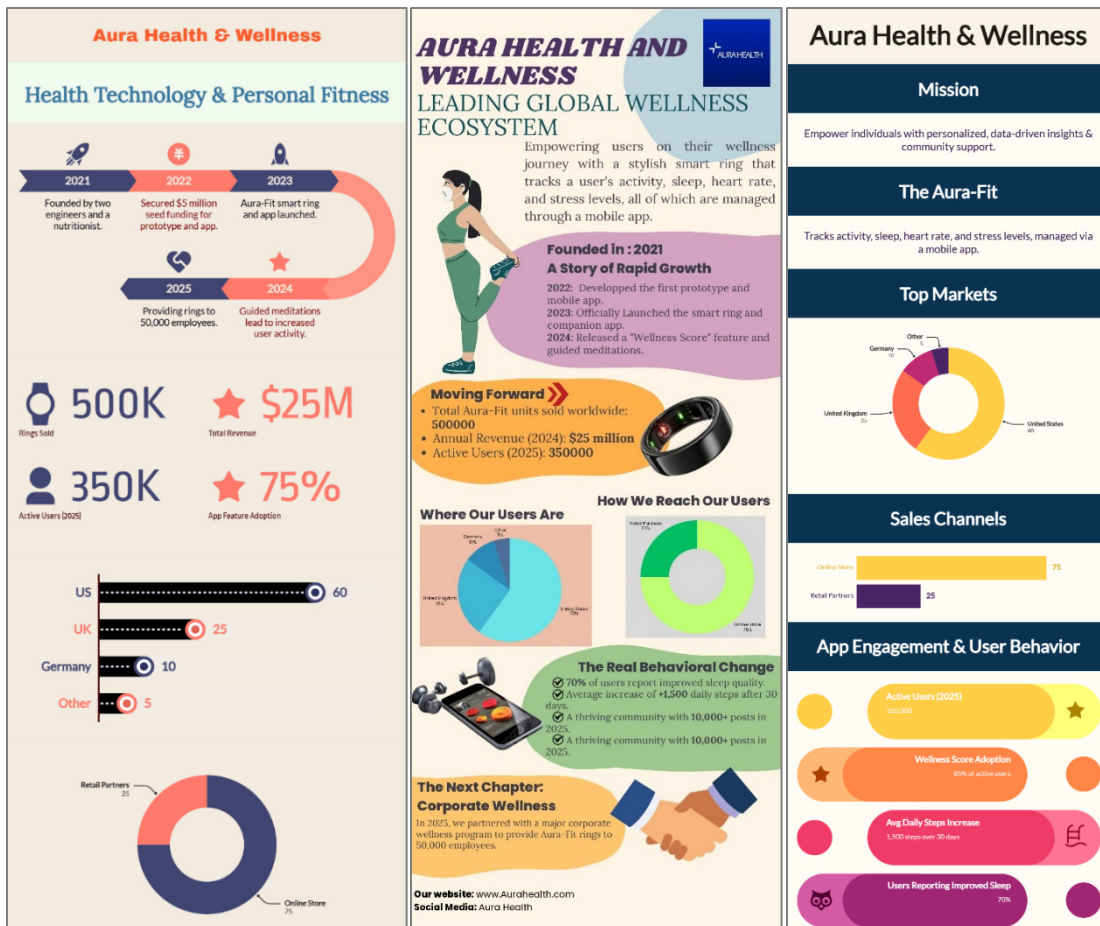


Figure 4. Sample infographics created by participants

Analysis

Data analysis was conducted in multiple stages. First, the internal consistency of the questionnaire items QA5 to QA12 was assessed using Cronbach's alpha, which demonstrated acceptable reliability for both undergraduate ($\alpha = 0.73$) and postgraduate ($\alpha = 0.79$) datasets.

To evaluate differences between the control and experimental groups, a series of Welch's t-tests was carried out. This comparative rubric evaluated infographic quality scores, questionnaire responses on usability and learning experience, and the time taken to complete the task. To further examine cohort-level effects, a two-way ANOVA was performed with students' level (undergraduate vs. postgraduate) and group (control vs. experimental) as factors.

Finally, the Creativity Support Index (CSI) was calculated to capture user perceptions of creativity support provided by the tools. CSI scoring involved computing factor scores and weighting them based on participants' stated importance ratings. Specifically, responses to CSI items were grouped under six factors: Enjoyment, Exploration, Expressiveness, Immersion, Results Worth Effort, and Collaboration. For each factor, the factor score (derived from related Likert-scale items) was multiplied by the corresponding importance weight provided by participants to obtain a weighted factor score. The overall CSI value for each group was computed by summing the weighted factor-score means and dividing by 3 to obtain an index score on a 100-point scale.

RESULTS

INFOGRAPHIC QUALITY

The total rubric scores showed a clear advantage for students in the experimental groups who used *Narrativ*. For undergraduates, the experimental group ($M = 86.79$, $SD = 5.93$) significantly outperformed the control group ($M = 64.48$, $SD = 12.72$), ($t(34.28) = -7.92$, $p < .001$, Cohen's $d = -2.25$) (Table 2 and Table 3). Similarly, postgraduate students in the experimental group ($M = 86.88$, $SD = 6.86$) scored significantly higher than their control counterparts ($M = 69.08$, $SD = 12.89$), ($t(38.73) = -6.16$, $p < .001$, Cohen's $d = -1.72$).

Across individual rubric dimensions, significant differences were observed in most areas (Figure 5). For undergraduates, the experimental group scored higher in Layout ($t(37.44) = -5.16$, $p < .001$), Visual Elements ($t(35.99) = -6.94$, $p < .001$), Color Selection ($t(44.56) = -4.56$, $p < .001$), Data Visualizations ($t(46.45) = -4.36$, $p < .001$), and Engagement and Impression ($t(41.64) = -4.86$, $p < .001$). Differences in Purpose and Relevance approached significance ($p = .073$), while Information Accuracy showed no significant difference ($p = .932$).

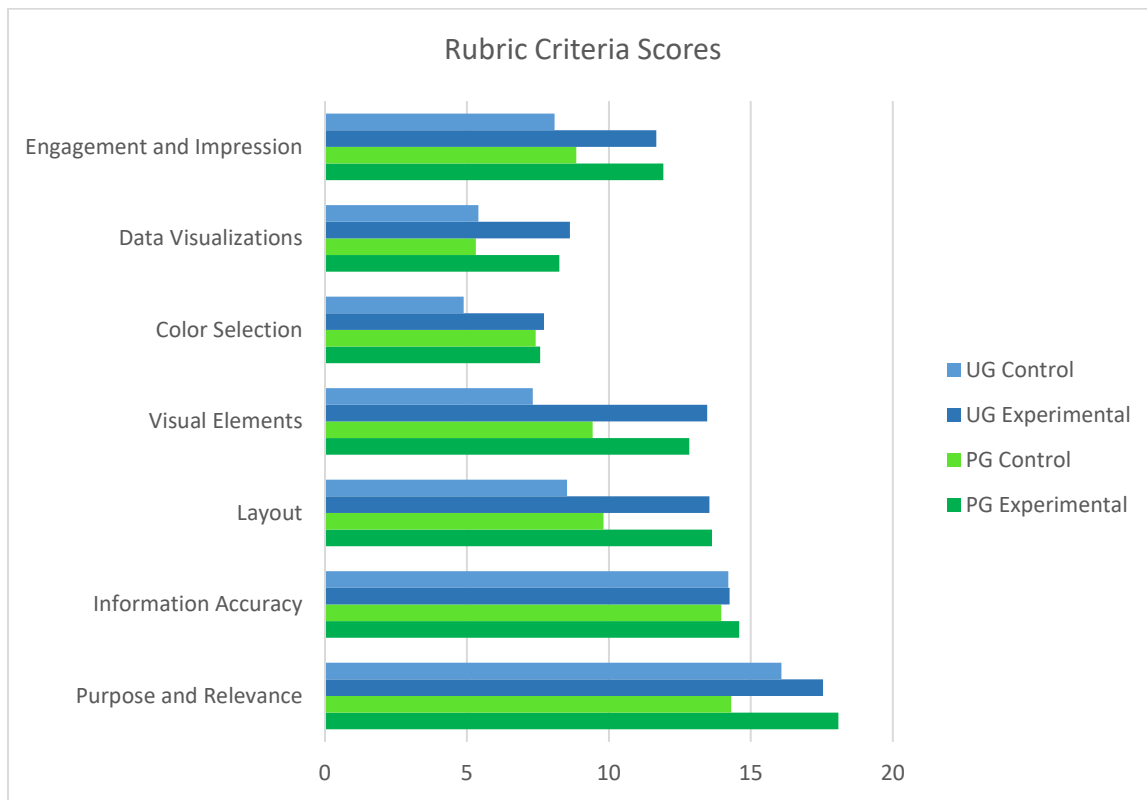
Postgraduate results showed a similar pattern (Table 2, Table 3, and Figure 5). The experimental group achieved significantly higher scores in Purpose and Relevance ($t(42.26) = -4.44$, $p < .001$), Layout ($t(43.59) = -6.08$, $p < .001$), Visual Elements ($t(37.79) = -3.73$, $p < .001$), Data Visualizations ($t(40.19) = -3.38$, $p = .002$), and Engagement and Impression ($t(38.82) = -4.14$, $p < .001$). No significant differences were found for Information Accuracy ($p = .207$) or Color Selection ($p = .792$).

Table 2. Group descriptives for evaluated infographic scores

Criterion	Group	Undergraduates			Postgraduates		
		N	Mean	SD	N	Mean	SD
Purpose and Relevance	Control	25	16.080	3.278	26	14.308	3.642
	Experimental	24	17.542	2.206	24	18.083	2.263
Information Accuracy	Control	25	14.200	2.363	26	13.962	2.144
	Experimental	24	14.250	1.648	24	14.583	1.176
Layout	Control	25	8.520	4.254	26	9.808	2.638
	Experimental	24	13.542	2.322	24	13.625	1.74
Visual Elements	Control	25	7.320	3.923	26	9.423	4.12
	Experimental	24	13.458	2.000	24	12.833	2.099
Color Selection	Control	25	4.880	2.455	26	7.423	2.564
	Experimental	24	7.708	1.853	24	7.583	1.64
Data Visualizations	Control	25	5.400	2.784	26	5.308	3.824
	Experimental	24	8.625	2.392	24	8.25	2.172
Engagement and Control	Control	25	8.080	3.068	26	8.846	3.307
	Experimental	24	11.667	2.014	24	11.917	1.767
Total	Control	25	64.480	12.715	26	69.077	12.893
	Experimental	24	86.792	5.934	24	86.875	6.861

Table 3. Welch's t-test for evaluated infographic scores

Criterion	Undergraduates				Postgraduates			
	t	df	p	Cohen's d	t	df	p	Cohen's d
Purpose and Relevance	-1.838	42.19	0.073	-0.523	-4.439	42.26	< .001	-1.245
Information Accuracy	-0.086	42.98	0.932	-0.025	-1.284	39.41	0.207	-0.36
Layout	-5.157	37.44	< .001	-1.466	-6.082	43.59	< .001	-1.708
Visual Elements	-6.94	35.99	< .001	-1.971	-3.729	37.79	< .001	-1.043
Color Selection	-4.564	44.56	< .001	-1.3	-0.265	42.91	0.792	-0.074
Data Visualizations	-4.355	46.45	< .001	-1.243	-3.377	40.19	0.002	-0.946
Engagement and Impression	-4.856	41.64	< .001	-1.382	-4.138	38.82	< .001	-1.158
Total	-7.921	34.28	< .001	-2.249	-6.157	38.73	< .001	-1.723

**Figure 5. Comparison of rubric criteria scores across groups**

The two-way ANOVA on total rubric scores revealed a significant main effect of group ($F(1,95) = 95.14, p < .001$), with experimental groups outperforming control groups. The main effect of students' level (undergraduate vs. postgraduate) was not significant ($F(1,95) = 1.30, p = .258$), nor was the interaction effect ($F(1,95) = 1.21, p = .275$). When analyzing specific criteria, Purpose and Relevance, Layout,

Visual Elements, Data Visualizations, and Engagement and Impression showed similar significant main effects of group.

The Color Selection dimension showed both significant main effects of group ($F(1,95) = 11.66, p < .001$) and students' level ($F(1,95) = 7.63, p = .007$), as well as a significant interaction ($F(1,95) = 9.29, p = .003$). This indicates that while experimental groups generally selected colors more effectively, postgraduates outperformed undergraduates, with the strongest improvements observed among undergraduates in the experimental condition.

TIME TAKEN TO COMPLETE THE TASK

The time required to complete the data storytelling activity differed significantly between control and experimental groups (Figure 6). For undergraduates, the control group took considerably longer ($M = 113.52$ minutes, $SD = 38.01$) than the experimental group ($M = 79.06$ minutes, $SD = 22.97$), ($t(39.73) = 3.86, p < .001$, Cohen's $d = 1.10$). A similar pattern was observed for postgraduates, where the control group ($M = 85.97$, $SD = 42.68$) also took significantly more time than the experimental group ($M = 53.62$, $SD = 18.49$) ($t(48) = 3.43, p = .001$, Cohen's $d = 0.97$).



Figure 6. Comparison of time taken to complete the task

The two-way ANOVA confirmed a strong main effect of group ($F(1,95) = 26.16, p < .001$), with experimental groups completing the task faster across both cohorts. A significant main effect of students' level was also found ($F(1,95) = 16.45, p < .001$), with undergraduates taking longer overall compared to postgraduates. The interaction effect was not significant ($F(1,95) = 0.03, p = .872$), suggesting that the time-saving benefit of the tool was consistent across both educational levels.

STUDENTS' PERCEPTIONS OF THE DESIGN TOOLS

Questions QA5 to QA12 of the exit questionnaire (see Appendix A - Questionnaire) measured the student perceptions of the design tool they used. For undergraduates, results indicated that the control group reported higher perceived ease and control with the tool. Significant differences were observed for QA5 - Ease of figuring out the tool ($t(36.92) = 2.69, p = .011$), QA6 - Availability of visual elements ($t(38.66) = 4.35, p < .001$), QA7 - Control over layout and visual elements ($t(39.22) = 7.15, p < .001$), and QA8 - Learning new layout structuring methods ($t(41.65) = 2.56, p = .014$). In each case, the control group reported higher agreement. No significant differences were found for QA9 – QA12.

For postgraduates, differences were less pronounced. Significant effects were found for QA6 ($t(38.40) = 4.24, p < .001$), and QA7 ($t(32.61) = 3.95, p < .001$), with control groups again reporting more positive perceptions. Other items showed no significant group differences.

CREATIVITY SUPPORT INDEX (CSI) RESULTS

For undergraduates, the control group reported a higher overall CSI score of 76.25 compared to the experimental group's 51.86. Welch's t-tests on the weighted factor scores showed significantly higher values for Exploration ($t(43.79) = 3.09, p = .004$) and Expressiveness ($t(43.99) = 4.08, p < .001$) factors for the control group. Weighted factor scores for other factors were also higher in the control group (Table 4), but not statistically significant.

Table 4. CSI results for the undergraduates

Factor	Control Group			Experimental Group		
	Ave. factor count (SD)	Ave. factor score (SD)	Ave. weighted factor score (SD)	Avg. factor count (SD)	Avg. factor score (SD)	Avg. weighted factor score (SD)
Enjoyment	2.46 (1.44)	16.25 (3.69)	39.75 (26.01)	2.55 (1.22)	10.45 (4.6)	28.36 (21.07)
Exploration	3.33 (1.17)	15.08 (3.59)	50.17 (21.04)	3.23 (1.07)	10.09 (4.55)	32.41 (17.95)
Expressiveness	3.00 (1.22)	15.08 (3.56)	43.50 (17.44)	2.64 (1.43)	9.64 (3.86)	23.50 (15.78)
Immersion	1.50 (1.22)	12.42 (4.84)	18.92 (20.03)	2.14 (1.36)	9.59 (4.46)	18.73 (13.76)
Results worth effort	3.13 (1.08)	15.63 (3.32)	50.25 (21.75)	2.95 (1.33)	11.50 (4.81)	36.77 (23.75)
Collaboration	1.58 (1.53)	15.50 (3.23)	26.17 (28.12)	1.50 (1.74)	8.82 (4.76)	15.82 (21.49)

When examining average factor scores, significant differences emerged across most dimensions: Enjoyment, Exploration, Expressiveness, Immersion, Results Worth Effort, and Collaboration (all $p < .05$), again showing that undergraduates perceived the traditional design tool more positively than the automated system (Figure 7).

For postgraduates, the control group again reported a higher overall CSI score of 79.69 than the experimental group's score of 63.68. Analysis of weighted factor scores indicated that the control group rated Exploration ($t(48.04) = 3.09, p = .003$) and Results Worth Effort ($t(42.69) = 3.29, p = .002$) significantly higher than the experimental group (Table 5). Enjoyment had a higher weighted factor score for the experimental group, but the difference was not statistically significant.

Average factor scores (Table 5 and Figure 7) also showed that postgraduates using control tools reported significantly greater Enjoyment ($p = .006$), Exploration ($p < .001$), Expressiveness ($p < .001$), Results Worth Effort ($p = .024$), and Collaboration ($p = .005$).

When comparing CSI scores between the undergraduate and postgraduate experimental groups, postgraduates had a higher overall CSI score of 63.68 compared to the undergraduate experimental group's 51.86. Based on the weighted factor scores, Enjoyment was significantly higher for postgraduates than undergraduates ($t(44.54) = 2.11, p = .040$). No significant differences were found for Exploration, Expressiveness, Immersion, Results Worth Effort, or Collaboration (all $p > .05$). Similarly, analysis of the unweighted factor scores identified a significant difference only for Enjoyment ($t(42.66) = 2.73, p = .009$) with the difference in Results Worth Effort reaching the significance threshold ($t(40.89) = 2.02, p = .050$).

Table 5. CSI results for postgraduates

Factor	Control group			Experimental group		
	Avg. factor count (SD)	Avg. factor score (SD)	Avg. weighted factor score (SD)	Avg. factor count (SD)	Avg. factor score (SD)	Avg. weighted factor score (SD)
Enjoyment	1.78 (1.48)	16.89 (2.99)	30.15 (26.01)	3 (1.22)	13.96 (4.14)	41.56 (21.69)
Exploration	3.89 (1.12)	16.37 (2.92)	62.93 (20.67)	3.68 (1.14)	11.56 (5.06)	43.92 (23.42)
Expressiveness	2.26 (1.1)	15.7 (2.92)	35.22 (18.73)	2.32 (1.03)	11.48 (4.29)	26.8 (14.62)
Immersion	1.59 (1.28)	13.93 (3.99)	22.15 (19.87)	1.28 (1.02)	11.4 (4.99)	15.64 (15.88)
Results worth effort	4.04 (0.9)	16.33 (2.65)	65.52 (16.96)	3.24 (1.33)	14.12 (3.97)	46.32 (24.16)
Collaboration	1.44 (1.45)	15 (3.69)	23.11 (23.08)	1.48 (1.53)	11.12 (5.55)	16.8 (18.31)

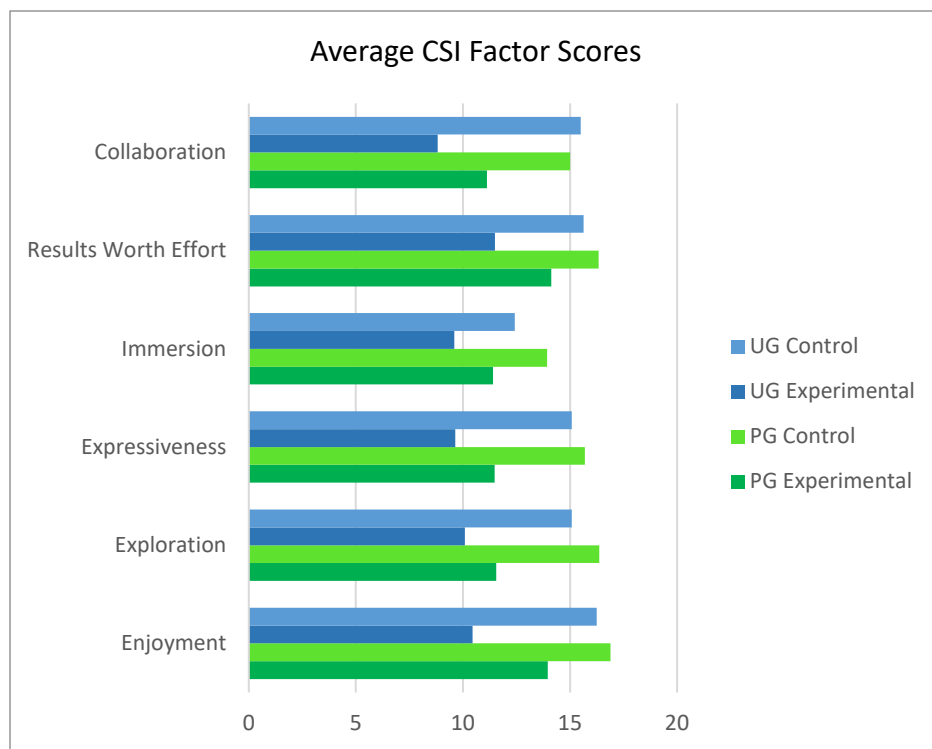


Figure 7. Comparison of average CSI factor scores across groups

OPEN-ENDED QUESTIONS

In the control groups, undergraduates and postgraduates alike emphasized usability, flexibility, and creative freedom and design options when reflecting on their experience with the traditional tool. They were consistently described as user-friendly and intuitive, with many appreciating the availability of ready-made templates in the tools that were ready to use. By contrast, students in the experimental groups mostly highlighted speed, automation, and novelty as the main advantages of the AI-based infographic

tool. Many participants appreciated how quickly *Narrativ* could generate visuals with minimal effort, describing it as “*an efficient way to create*” and mentioning that “*It auto-generates graphics within seconds.*”

When examining the challenges, participants in the control group most frequently mentioned restrictions related to the traditional tools’ feature limitations due to license models. Several respondents expressed frustration that many useful templates, icons, and features were only available in the premium versions, hindering their ability to utilize the tools for the task fully. While most found the traditional tool intuitive overall, a few found the range of options overwhelming, with one participant noting, “*due to the variety of options, it was hard to choose one.*” In the experimental group, concerns were mainly about limited customization options and a lack of control over the layout. Many respondents mentioned that “*I was not able to change it according to my requirements*” and that “*when we want to modify it, we can’t do the data modifications for the same infographic — it generates a new one with new features.*” Students repeatedly emphasized the need to make small adjustments, with comments such as “*editing the visuals individually.*”

DISCUSSION

The purpose of this study was to evaluate the effectiveness of an AI-based infographic generation tool in a higher education context. Specifically, the research examined whether the use of the tool enhanced infographic quality, improved task efficiency, supported positive user experiences, fostered creativity, and influenced students’ sense of agency and control during the infographic design process compared to traditional template-based design approaches.

EFFECT ON THE QUALITY OF INFOGRAPHICS

The findings clearly indicate that the AI-based infographic generation tool *Narrativ*, significantly improved the overall quality of student-created infographics compared to the traditional tool. Across both undergraduate and postgraduate cohorts, the experimental groups consistently achieved higher total rubric scores than the control groups. The improvements were particularly pronounced in criteria related to layout, visual elements, data visualizations, and overall engagement, where experimental groups scored substantially higher. These results suggest that the AI tool’s automated support effectively addressed common challenges students face in visual design, such as achieving balance, maintaining visual appeal, and selecting appropriate color schemes (S. Zhu et al., 2020; W. Zhu et al., 2024). A common issue observed with the infographics created by the control groups was that they contained too much textual information, which is also another common issue students face (Jaleniauskiene & Kasperuniene, 2024) when creating infographics.

Interestingly, the accuracy of information did not differ significantly between groups. This finding suggests that while the AI tool enhanced the presentation of the data story, the story’s quality and accuracy remained dependent on the students’ own analytical skills. These results are consistent with prior work on automated visualization systems (Y. Wang et al., 2020; Wu et al., 2022; S. Zhu et al., 2020), which emphasizes their potential to improve accessibility and reduce barriers for non-expert users. By automating low-level design decisions, such tools free learners to focus more on content analysis and storytelling.

EFFECT ON TASK EFFICIENCY

The results also demonstrate that the AI-based tool substantially reduced the time students needed to complete their infographic assignments. Both undergraduate and postgraduate experimental groups finished the task significantly faster than their counterparts using the traditional tool. Similar effects have also been observed with other automated visualization tools, such as DataShot (Y. Wang et al., 2020) and Retrieve-Then-Adapt (Qian et al., 2021). The ANOVA results further confirmed that this time-saving benefit was consistent across cohorts, with no interaction effects, suggesting that the efficiency gain generalizes to different student populations.

This finding is important because infographic design is typically a time-intensive process that requires careful choices about layout, typography, color, and data visualization. By automating many of these design elements, the tool alleviated some of the manual effort required of students and may have allowed them to focus more on organizing information and crafting the narrative. Such efficiency aligns with theories of cognitive load reduction in educational technology, in which support is provided to a learner as scaffolding to reduce task complexity (van Nooijen et al., 2024). This allows the learners to allocate their cognitive resources more effectively to higher-order thinking.

PERCEIVED USABILITY AND CREATIVITY SUPPORT

When examining how students perceived the AI-based tool's usability and creativity support relative to the conventional tool, the results reveal an interesting picture. While the AI-based tool improved the efficiency and rubric-evaluated quality of the infographics produced, students' perceptions of its usability and creativity support were not uniformly positive. Questionnaire results indicated that control groups – those using the conventional design tool – reported higher levels of perceived control over layout and visual elements (QA6, QA7) and greater confidence in their design process. In contrast, students in the experimental group, although producing higher-quality infographics, felt less in control of design decisions and less confident in their ability to shape the outcome.

Creativity Support Index (CSI) results provide further insight. For undergraduates, the experimental group achieved a lower CSI score (51.86) compared to the control group (76.25), suggesting that novice learners felt more creative and expressive when using conventional tools. For postgraduates, the gap was smaller (control = 79.69; experimental = 63.68), implying that more advanced learners were better able to integrate the AI tool into their creative process. Factor-level comparisons showed that, while the AI-based tool provided higher but non-significant Enjoyment, at least for advanced learners, it scored lower on Exploration and Expressiveness, again pointing to the constraints students experienced in feeling personally creative.

This highlights a potential trade-off between automation and perceived agency, the degree to which a person feels they have control over their actions and decisions. This is important in an educational context as it affects students' beliefs about their ability to influence their learning experiences (Smith, 2018). Automation may make the design process less complex and enhance final outputs, but it can also make learners feel distanced from the creative act, as if the tool is doing the design for them. Such perceptions can limit satisfaction, even when the final product is objectively better. Similar concerns were raised in other automated visualization research, such as DataShot (Y. Wang et al., 2020), where users noted that auto-generation could limit their expressiveness.

DIFFERENCES IN THE ADOPTION AND PERCEPTION OF THE TOOL BETWEEN COHORTS

The comparison across cohorts shows meaningful differences in how undergraduates and postgraduates adopted and perceived the AI-based tool. In terms of objective outcomes, both groups benefited from significant improvements in rubric scores for infographics created using the AI tool compared with those created using conventional tools. This suggests that the tool was effective across study levels in improving the quality of infographic outputs.

However, subjective perceptions of the tool's effectiveness differed between the two cohorts. Undergraduates reported lower Creativity Support Index (CSI) scores when using the AI-based tool than when using the conventional tool. This suggests they felt less creative, expressive, and immersed in the task. In contrast, while postgraduates also scored lower on the CSI in the experimental condition, the difference was less pronounced. Factor-level comparisons suggest that postgraduate students using the AI-based tool experienced greater enjoyment, while perceptions of the other dimensions of creativity support were broadly comparable across the two cohorts. A plausible explanation is that their greater prior experience with academic tasks and design tools enabled them to use the AI system as a scaffold rather than a creative constraint.

The ANOVA results further support this interpretation. The two cohorts did display significant main effects of the tool on rubric scores and time taken for the task, but no interaction effects were observed. This indicates that the tool provided equal measurable benefits to both groups. The difference lay in subjective perceptions: undergraduates were more inclined to view automation as limiting their creativity, whereas postgraduates appeared better able to balance efficiency with personal expression. This behavior in postgraduates might be attributed to their employment in business analytics and related fields, where proficiency with automated tools is often essential. Studies show that learners who are confident in using AI-based tools for productivity are more likely to use them frequently (Ahn, 2024).

These results suggest that learner maturity and prior experience play important roles in how learners perceive AI-based educational tools. With less experienced learners, there is a possibility that the tool is perceived as too restrictive, and as a consequence, could negatively impact the learner's motivation and creativity. It is often challenging for a fully auto-generated visualization to perfectly meet user needs; thus, there must be sufficient flexibility for human interaction to refine the output (Zhu-Tian et al., 2020). For advanced learners, the same tool may be viewed as a useful accelerator that complements their existing skills. Thus, it is important to tailor such tools to students' developmental stage, allowing creative exploration for novice learners and efficiency for more advanced learners.

Another important implication of these findings concerns the nature of learning when AI-supported design tools are introduced into educational settings. While the observed improvements in infographic quality and task efficiency demonstrate the value of automation, they also raise questions about which skills students are actually developing during the design process. Traditional infographic creation requires learners to make deliberate decisions about hierarchy, balance, alignment, color harmony, and information flow, all of which contribute to the development of visual literacy. Consequently, educators need to carefully consider how AI-supported tools can be integrated without diminishing these learning opportunities. Rather than treating AI-generated outputs as final products, instructional activities could encourage students to critically evaluate, justify, and refine AI suggestions, thereby transforming the tool from a design substitute into a learning scaffold. Such an approach would allow students to benefit from the efficiency gains of automation while still developing a deeper understanding of the design principles that underpin effective visual communication.

CONCLUSION

This study examined the role of AI-based infographic generation in business analytics education. We developed an automated infographic generation tool, *Narrativ*, and using controlled experiments with both undergraduate and postgraduate students, we evaluated the impact of this tool on infographic quality, task efficiency, user perceptions, and creativity support.

Overall, the study demonstrates that AI-based infographic tools are highly effective for data storytelling at improving quality and efficiency, making them valuable in academic and professional contexts where time and clarity are critical. By automating design elements such as layout, balance, and color selection, the tool reduced the time and manual effort required for design. It may have provided students with additional capacity to focus on content analysis and storytelling. However, a creativity–efficiency paradox emerged: while outputs improved, many students, especially undergraduates, felt less agency and expressiveness when working with the AI system. These findings indicate that while AI-based tools can accelerate design and improve outcomes, their educational value depends heavily on how well they preserve student agency, support critical design decision-making, and provide sufficient opportunities to express creativity. For adoption to be sustainable, such tools need to balance efficiency with mechanisms that preserve or enhance learners' sense of ownership in the creative process.

This study has several limitations that should be acknowledged. It was based on a single task (the Aura Health & Wellness case study), which limits the generalizability of findings. Additionally, only one AI-based infographic generation tool was evaluated, and results may differ with tools that offer different balances between automation and user control. The control condition relied exclusively on Canva;

therefore, the findings may not generalize to comparisons with other conventional design tools that offer different features, workflows, or levels of design flexibility. Most participants were familiar with Canva, whereas Narrativ was new to them, and this difference in prior experience may have influenced the usability and creativity-support findings. Furthermore, the sample consisted solely of business analytics students from two cohorts, which limits its applicability to other disciplines or experience levels. Future research should therefore include broader participant groups, explore a range of AI systems, and investigate how learners from different backgrounds engage with automated tools for creative visualization.

An additional limitation relates to the rubric-based evaluation process. A single expert evaluator conducted the assessment. Although a blind marking procedure was used to reduce potential bias, the absence of multiple raters prevented the calculation of inter-rater reliability. Consequently, the quality scores reflect the judgment of one expert and may be influenced by individual evaluation preferences. Future studies should employ multiple independent raters and report inter-rater agreement measures to further strengthen the reliability of infographic quality assessments.

Further studies are needed to examine the long-term effects of AI-based tools on learning and creativity development. Longitudinal research could reveal whether initial reductions in perceived creativity are temporary as students learn to use automation more effectively. Future directions include developing adaptive AI systems that adjust levels of guidance based on user proficiency and exploring how such tools can enhance collaborative creativity – an essential skill in business analytics. Ultimately, while AI-driven infographic tools show strong potential to improve data storytelling and communication, educators must ensure they complement, rather than constrain, students' creativity, agency, and critical thinking as they transform data into meaningful insights.

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APPENDIX A - QUESTIONNAIRE

QA1. Your index number:

QA2. What is the primary tool you used to create the infographic for this task?

QA3. Previous experience with data visualization:

- ☐ Beginner (no/little prior experience)
- ☐ Intermediate (some coursework/project use)
- ☐ Advanced (regular use, strong skills)

QA4. Familiarity with infographic/visual design tools:

- ☐ Power BI
- ☐ Tableau
- ☐ Canva
- ☐ PowerPoint
- ☐ Piktochart
- ☐ Other:

Please rate how much you agree with the following statements on a scale from 1 (strongly disagree) to 7 (strongly agree).

QA5. I could figure out how to use the infographic design tool I used, without much help.

QA6. The tool I used offered visual elements (charts, icons, graphical elements, etc.) that matched my needs.

QA7. I felt in control of layout, typography, and visual elements.

QA8. I learned new ways to structure an infographic.

QA9. It was difficult to decide how to present the information visually.

QA10. I found this activity mentally demanding.

QA11. I could create a visually appealing infographic.

QA12. I felt confident that my final infographic looked professional.

In this section, you will see 12 statements about your experience using the primary tool you used for this activity. For each statement, please rate how much you agree with it on a scale from 0 to 10 based on your personal experience:

0 = Highly disagree

5 = Neutral

10 = Highly agree

QB1. I would be happy to use this tool regularly for creating infographics.

QB2. I enjoyed using the tool for this task.

QB3. It was easy for me to explore many different ideas, layouts, or visual styles using this tool.

QB4. The tool was helpful in allowing me to track different ideas, outcomes, or design possibilities.

QB5. I was able to be very creative while doing the activity inside this tool.

QB6. The tool allowed me to be very expressive visually.

QB7. My attention was completely focused on creating the infographic, and I forgot about the tool that I was using.

QB8. I was so engaged in the activity that I forgot about the tool that I was using.

QB9. I was satisfied with what I was able to create with the tool.

QB10. The infographic I created was worth the time and effort I put into making it.

QB11. The tool allowed others to collaborate with me easily.

QB12. It was easy to share my ideas and infographic designs with others through this tool.

In the following section, you will see a series of paired comparisons between two aspects of the tool you just used. Each pair will be presented in the form of the statement:

“When doing this task, it’s most important that I’m able to ...”

You will then see two possible completions of the statement, each describing a different factor (for example: be able to explore many different ideas vs. be able to clearly understand what the tool is doing).

Choose the one that feels more important to you when working on the given task. You will answer 15 comparisons in total.

QC1. When doing this task, it’s most important that I’m able to ...

☐ Be creative and expressive ☐ Become immersed in the activity

QC2. When doing this task, it’s most important that I’m able to ...

☐ Be creative and expressive ☐ Enjoy using the system or tool

QC3. When doing this task, it’s most important that I’m able to ...

☐ Be creative and expressive ☐ Explore many different ideas, outcomes, or possibilities

QC4. When doing this task, it’s most important that I’m able to ...

☐ Be creative and expressive ☐ Produce results that are worth the effort I put in

QC5. When doing this task, it’s most important that I’m able to ...

☐ Be creative and expressive ☐ Work with other people

QC6. When doing this task, it's most important that I'm able to ...

- ☐ Become immersed in the activity ☐ Enjoy using the system or tool

QC7. When doing this task, it's most important that I'm able to ...

- ☐ Become immersed in the activity ☐ Explore many different ideas, outcomes, or possibilities

QC8. When doing this task, it's most important that I'm able to ...

- ☐ Become immersed in the activity ☐ Produce results that are worth the effort I put in

QC9. When doing this task, it's most important that I'm able to ...

- ☐ Become immersed in the activity ☐ Work with other people

QC10. When doing this task, it's most important that I'm able to ...

- ☐ Enjoy using the system or tool ☐ Explore many different ideas, outcomes, or possibilities

QC11. When doing this task, it's most important that I'm able to ...

- ☐ Enjoy using the system or tool ☐ Produce results that are worth the effort I put in

QC12. When doing this task, it's most important that I'm able to ...

- ☐ Enjoy using the system or tool ☐ Work with other people

QC13. When doing this task, it's most important that I'm able to ...

- ☐ Explore many different ideas, outcomes, or possibilities ☐ Produce results that are worth the effort I put in

QC14. When doing this task, it's most important that I'm able to ...

- ☐ Explore many different ideas, outcomes, or possibilities ☐ Work with other people

QC15. When doing this task, it's most important that I'm able to ...

- ☐ Produce results that are worth the effort I put in ☐ Work with other people

In this section, we'd like to hear your thoughts in your own words. Please share as much detail as you feel comfortable. Your answers will help us better understand your experience with the tool.

QD1. What did you like most about using the tool you used for this activity?

QD2. What did you find challenging or frustrating about the tool?

APPENDIX B – INFOGRAPHIC EVALUATION RUBRIC

Criterion	Excellent	Good	Fair	Poor	Marks
1. <i>Clear purpose and relevance to target audience</i>	Presents a crystal-clear purpose and focus; perfectly tailored to the intended audience (20 marks)	Purpose is clear and mostly aligned to the target audience, with minor lapses (13 marks)	Purpose is somewhat vague; relevance to audience only partly achieved (7 marks)	Purpose is unclear or irrelevant to the audience (0 marks)	20

Criterion	Excellent	Good	Fair	Poor	Marks
<i>2. Information accuracy and reliability</i>	All information is accurate, reliable, and well-referenced; no errors (15 marks)	Information is mostly accurate and reliable; only minor issues (10 marks)	Contains noticeable inaccuracies or weak reliability of some content (5 marks)	Major inaccuracies or unreliable information undermine credibility (0 marks)	15
<i>3. Layout, balance, and clutter</i>	Layout is well-structured, balanced, and free from clutter; excellent visual flow (15 marks)	Layout is mostly organized and balanced, though slightly crowded in places (10 marks)	Layout shows some imbalance or clutter that distracts from the message (5 marks)	Layout is cluttered, confusing, or lacks structure. (0 marks)	15
<i>4. Visual elements for comprehension and engagement</i>	Visuals are engaging, purposeful, and enhance comprehension and recall (15 marks)	Visuals are clear and engaging but only somewhat enhance comprehension (10 marks)	Visuals are used but with limited effectiveness in supporting the message (5 marks)	Visuals are irrelevant, distracting, or absent (0 marks)	15
<i>5. Color selection</i>	Colors are deliberately chosen, harmonious, and strongly enhance appeal and memorability (10 marks)	Colors are appropriate and enhance appeal, with minor mismatches (7 marks)	Colors are somewhat effective but inconsistent or overused (3 marks)	Poor or distracting color choices reduce effectiveness (0 marks)	10
<i>6. Appropriate data visualizations</i>	Data is presented with highly suitable, accurate, and clear visualizations (10 marks)	Data visualizations are appropriate but could be more effective (7 marks)	Visualizations are partially appropriate or somewhat unclear (3 marks)	Data visualizations are unsuitable, misleading, or missing (0 marks)	10
<i>7. Engagement and first impression</i>	Infographic is highly engaging, aesthetically striking, and leaves a strong positive impression (15 marks)	Infographic is engaging and visually appealing, leaving a generally good impression (10 marks)	Infographic is moderately engaging; impression is average (5 marks)	Infographic lacks engagement or visual appeal; weak first impression (0 marks)	15

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