

DS-LAK24

Third workshop on Data Storytelling and Learning Analytics Dashboards



MONASH
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Organisers



Gloria Milena Fernandez-Nieto
Monash University, Australia



Vanessa Echeverria
Monash University, Australia



Roberto Martinez-Maldonado
Monash University, Australia



Yi-shan Tsai
Monash University, Australia



Lu Lawrence
Utah State University, USA



Shaveen Singh
Monash University, Australia



Stanislav Pozdniakov
The University of Queensland,
Australia



Lujie Karen Chen
University of Maryland Baltimore
County, USA



Jiaqi Gong
The University of Alabama, USA



Louise Yarnall
SRI Education, USA

Agenda

Time	Duration	Activity	Responsible
1:30 - 1:45 PM	15 min	Introduction	All
1:45 - 2:15 PM	30 min	Welcome and contextualisation of existing work on DS	Organisers
2:15 - 3:00 PM	45 min	Methods and Methodologies for DS in LA Dashboards. 5 min presentation + 5 min for questions	Participants
3:00 - 3:30 PM	30 min	Coffee break	
3:30 - 3:45 PM	15 min	Methods and Methodologies for DS in LA Dashboards. 5 min presentation + 5 min for questions	Participants
3:45 - 4:45 PM	1 hour	Follow up discussion	All
4:45 - 5:00 PM	15 min	Wrap up	All

Introductions

15 minutes



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Introductions

- A. Introduce yourself (name, country, and university)**

- B. Slido: What do you want to learn from this workshop?**

Options to access the Slido poll:

- Go to <https://slido.com> enter this code: 3604266
- Visit: <https://shorturl.at/hqwPY>
- Or scan de QR code



Data Storytelling and Learning Analytics Dashboards - A brief introduction

30 minutes



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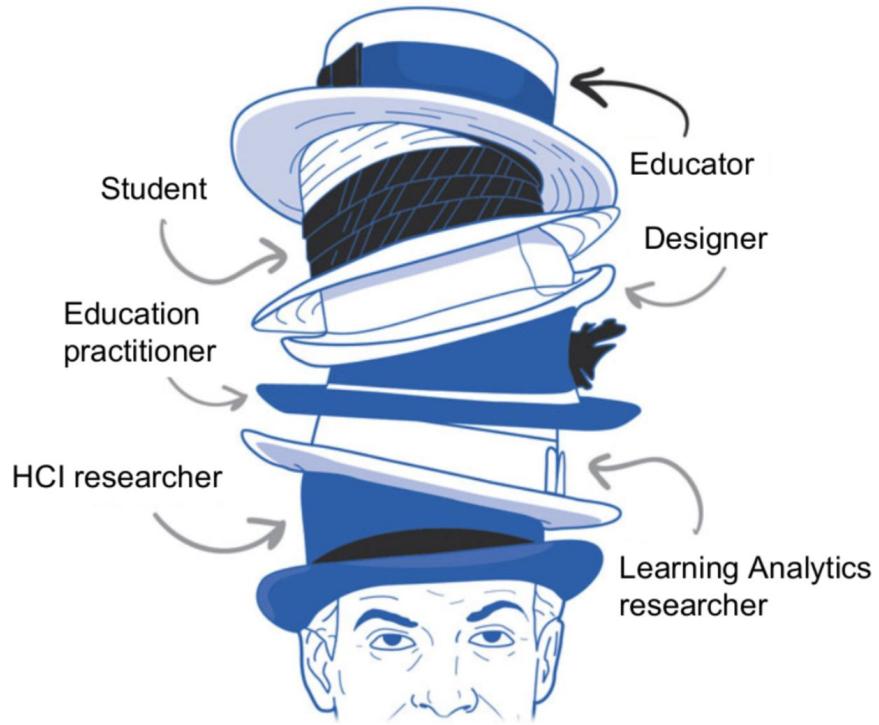
Agenda

- Motivation and foundations
- Previous and current LA work

Motivations and foundations

Motivations and foundations

Data Storytelling sits at the intersection of various **areas of expertise** (InfoVis, HCI, design, storytelling, psychology)



... we will be wearing multiple hats.

Motivations and foundations

"we are drowning in
information [data], but we
are starved for
knowledge".

John Naisbitt , 1982



Motivations and foundations



= INSIGHT

Motivations and foundations

WHAT IS

An information **compression** technique for communicating **insights** to an audience through the combination of **data**, **visuals**, and **narrative**.



Motivations and foundations

1 Data Collection



2 Data Preparation



3 Data Visualization



4 Data Analysis



5 Data Storytelling



*"The journey of going from raw data to a data story is a **process**. Successful data storytelling doesn't begin at step five—it begins right at the beginning with the data you collect"*

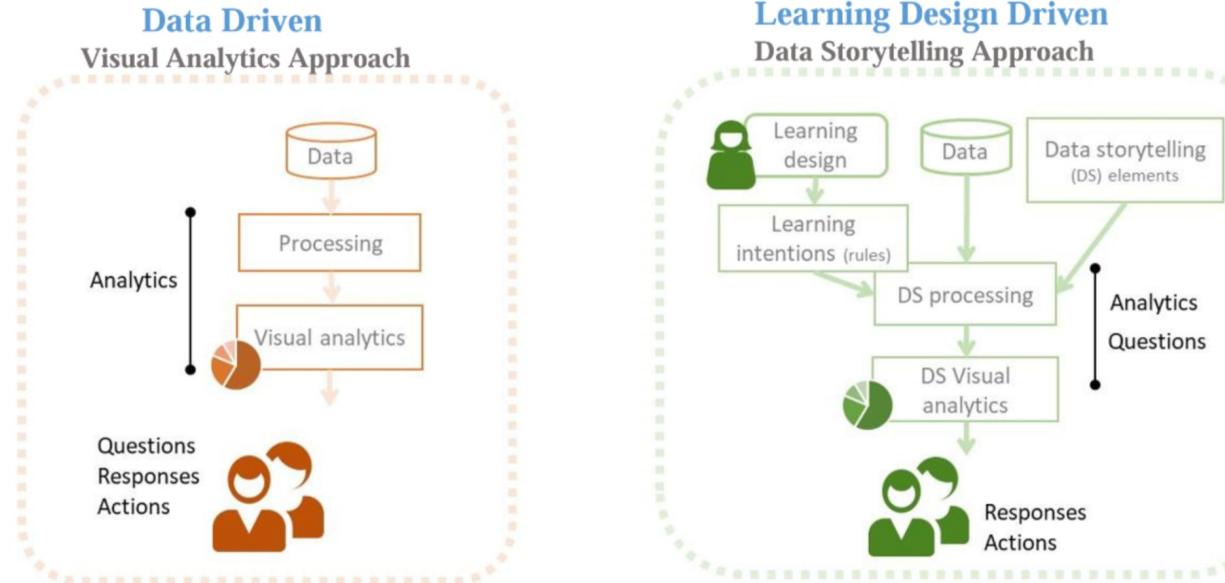
Previous and current DS-LA work

Data Storytelling **to communicate insights** (Info Visualisation)

Previous and current DS-LA work



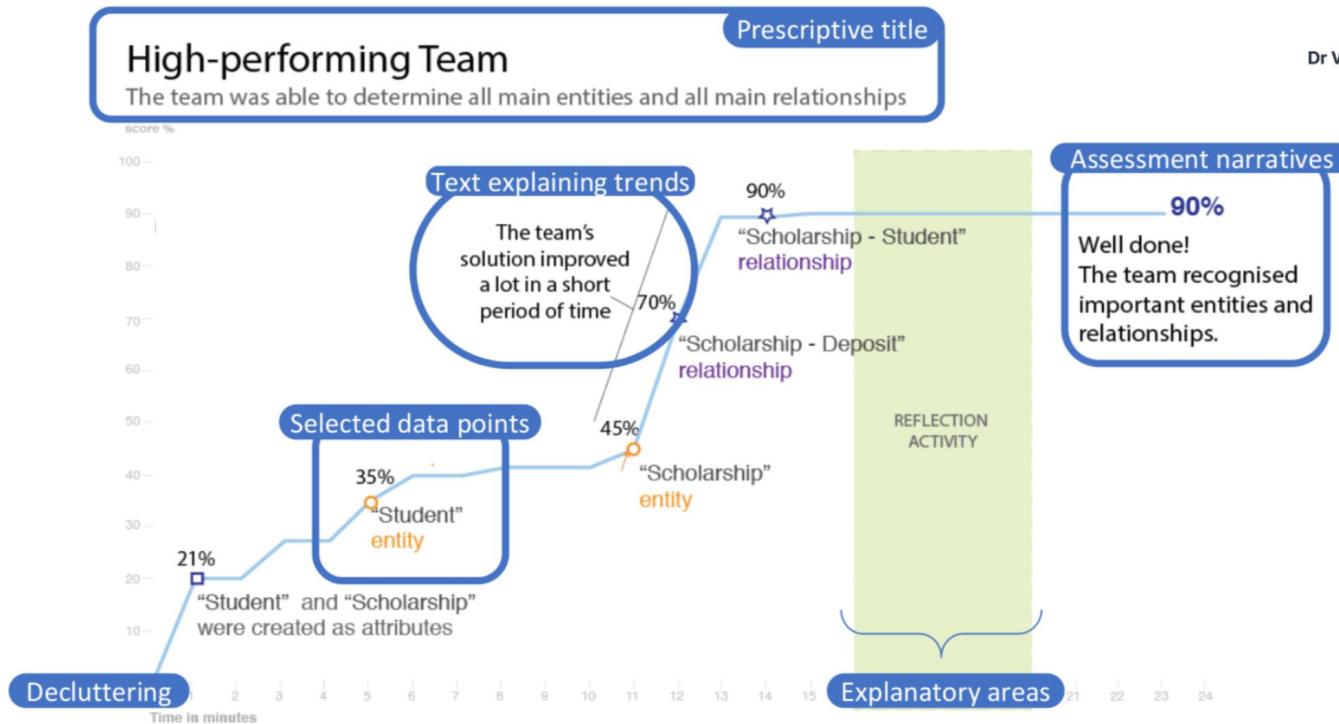
Dr Vanessa Echeverria



Previous and current DS-LA work



Dr Vanessa Echeverria



Previous and current DS-LA work



Dr Roberto Martinez-Maldonado



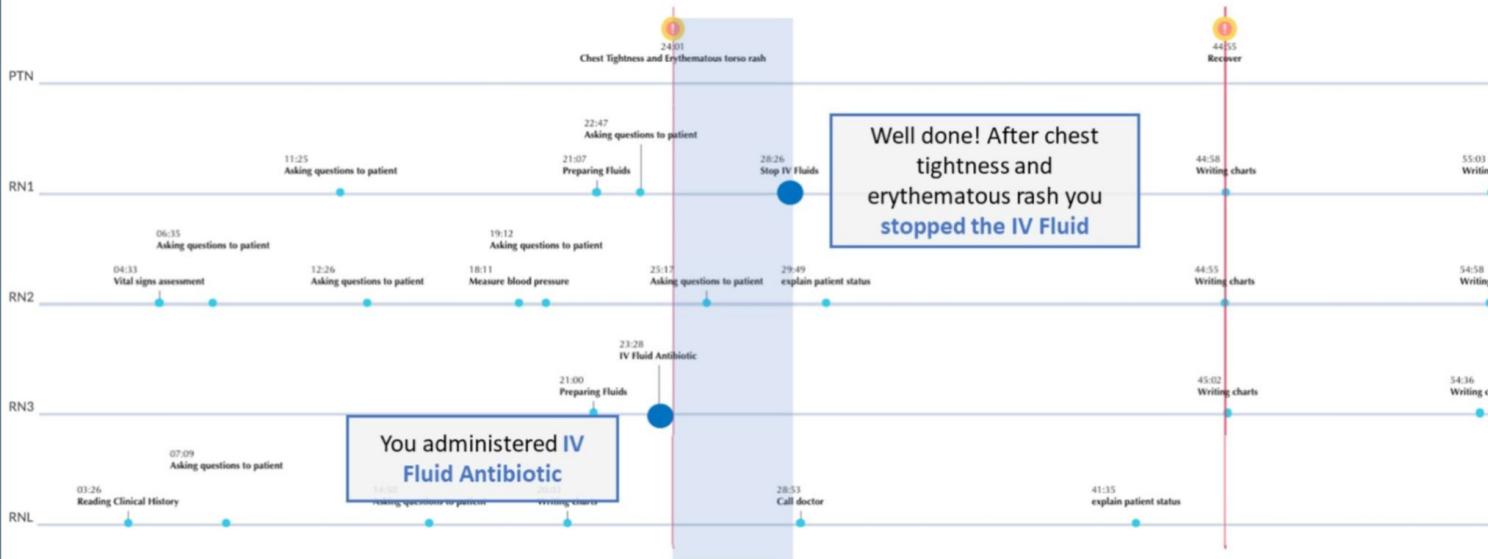
“The goal of MMLA is to support learning experiences that may be collaborative, hands-on, and face-to-face, **de-emphasizing the computer screen** as the primary form or object of interaction”

Previous and current DS-LA work



Dr Roberto Martinez-Maldonado

RN1 stopped the medication **less than 5 minutes** after patient's adverse reaction



Martinez-Maldonado & Echeverria, & Fernandez-Nieto & Buckingham Shum (2020). **From Data to Insights: A Layered Storytelling Approach for Multimodal Learning Analytics.** 1-15.
10.1145/3313831.3376148

Vital Signs Assessment

Administer and Stop IV Antibiotic

Perform ECG

Call the doctor

Arousal

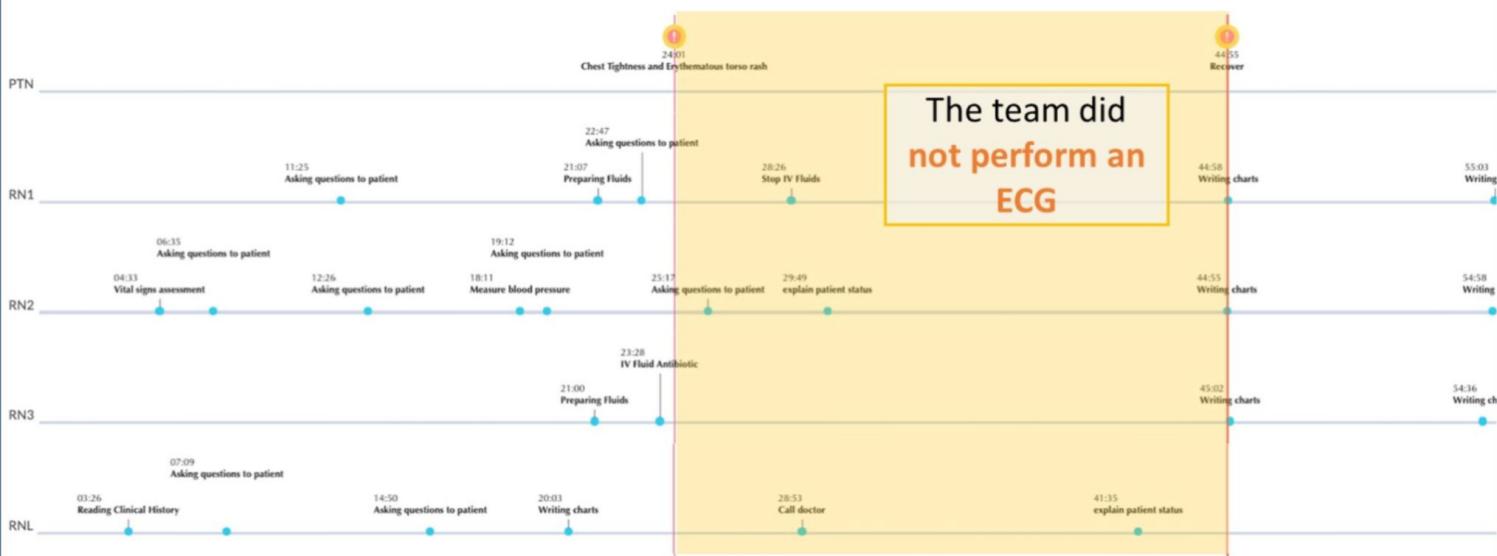
Previous and current DS-LA work

DS to communicate insights

It is recommended to **perform an ECG** after the patient complains of chest tightness



Dr Roberto Martinez-Maldonado



Martinez-Maldonado & Echeverria, & Fernandez-Nieto & Buckingham Shum (2020). **From Data to Insights: A Layered Storytelling Approach for Multimodal Learning Analytics.** 1-15.
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Vital Signs Assessment

Administer and Stop IV Antibiotic

Perform ECG

Call the doctor

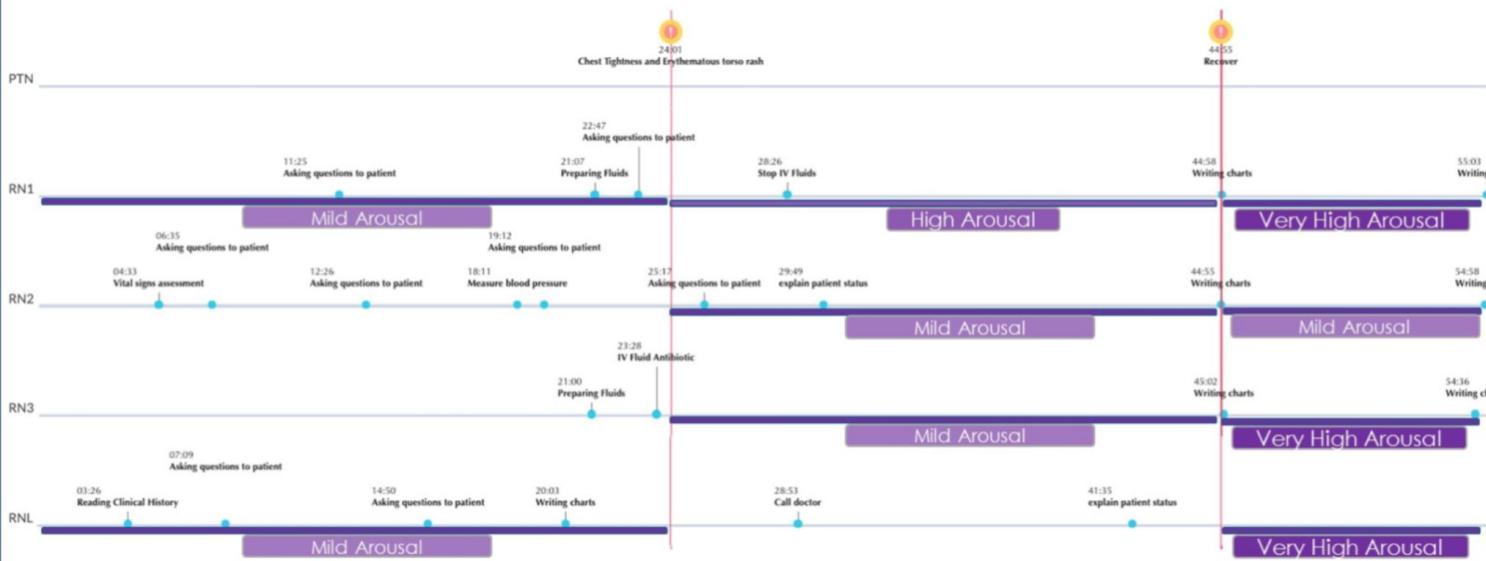
Arousal

Previous and current DS-LA work



Dr Roberto Martinez-Maldonado

RN1, RN3 and RNL presented **several arousal peaks** throughout the simulation
RN2 presented **a few arousal peaks**



Martinez-Maldonado & Echeverria, & Fernandez-Nieto & Buckingham Shum (2020). **From Data to Insights: A Layered Storytelling Approach for Multimodal Learning Analytics.** 1-15.
10.1145/3313831.3376148

Vital Signs Assessment

Administer and Stop IV Antibiotic

Perform ECG

Call the doctor

Arousal

Previous and current DS-LA work

KEY: • TITLE • HIGHLIGHT • CAPTIONS • NARRATIVE

A. Data Storytelling Editor

Proximity | Title for the criteria:
Team response after allergic reaction (patient-care)

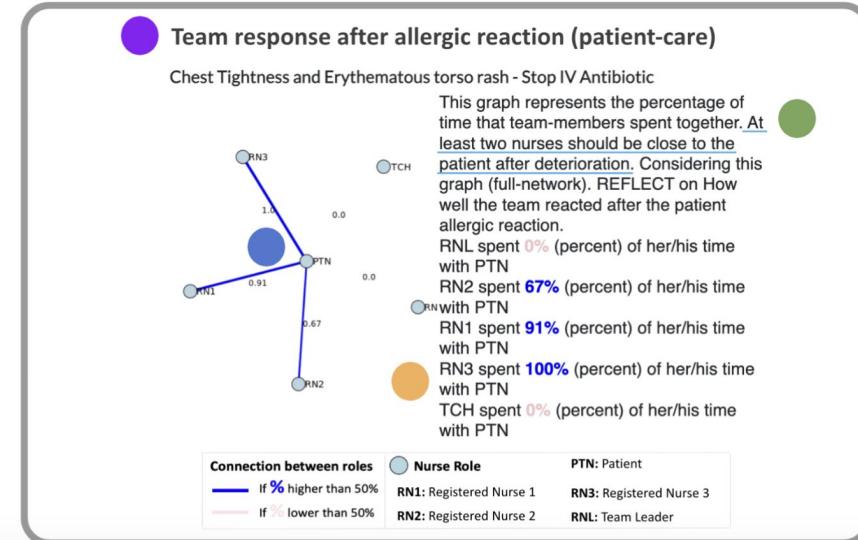
Action (A): Chest Tightness and Erythematous torso rash || PTN || Action (B): Stop IV Antibiotic

Feedback
This graph represents the percentage of time that team-members spent together.
At least two nurses should be close to the patient after deterioration.
Considering this graph (full-network). REFLECT on How well the team reacted after the patient allergic reaction.



Dr Gloria Milena Fernández-Nieto

B. Learning Analytics Dashboard Narrative



Fernandez-Nieto, Martinez-Maldonado, Echeverria, Kitto, Gašević, and Buckingham Shum. 2024. **Data Storytelling Editor: A Teacher-Centred Tool for Customising Learning Analytics Dashboard Narratives.**

In LAK '24, March 18–22, 2024, Kyoto, Japan. ACM, New York, NY, USA, 16 pages

Previous and current DS-LA work



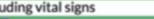
Dr Gloria Milena Fernández-Nieto

Create Rule

I Give feedback based on FREQUENCY of actions  **Assessment criteria type**

Name this rule:
Frequent Systematic Assessment

This action [A]: g. Bed 4. Systematic Assessment including vital signs

Should take place every: 5 (minutes)  **meta-information** 

Feedback message if done correctly:
Well done. The team systematically assessed the deteriorating patient using a primary assessment including vital signs.

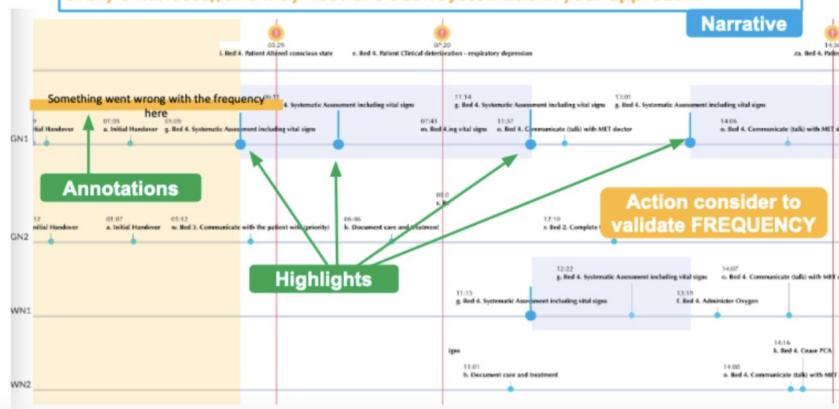
V Feedback message if done incorrectly:
Unfortunately, the patient assessment was not completed in a timely manner (i.e. every 5 minutes), and may not have been systematic in your approach.
Remember to use **DRSABCDE**.

Save Criteria  **Feedback messages**

Add assessment item (rule)

B - Data story about Systematic assessment

fre Unfortunately, the patient assessment was not completed in a timely manner (i.e. every 5 minutes), and may not have been systematic in your approach.



Fernandez-Nieto, Martinez-Maldonado, Echeverria, Kitto, Gašević, and Buckingham Shum. 2024. **Data Storytelling Editor: A Teacher-Centred Tool for Customising Learning Analytics Dashboard Narratives.**

In LAK '24, March 18–22, 2024, Kyoto,
Japan. ACM, New York, NY, USA, 16 pages

Previous and current DS-LA work



Dr Stanislav Pozdniakov

7:35pm

Main Room

Activity 1

Main Room

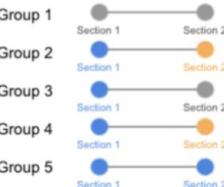
Activity 2

8:42pm

Are there students **inactive** in Zoom?

- Group 1 All inactive
- Group 2 2 inactive
- Group 3 All active
- Group 4 Single Person Talking Too Much
- Group 5 All active

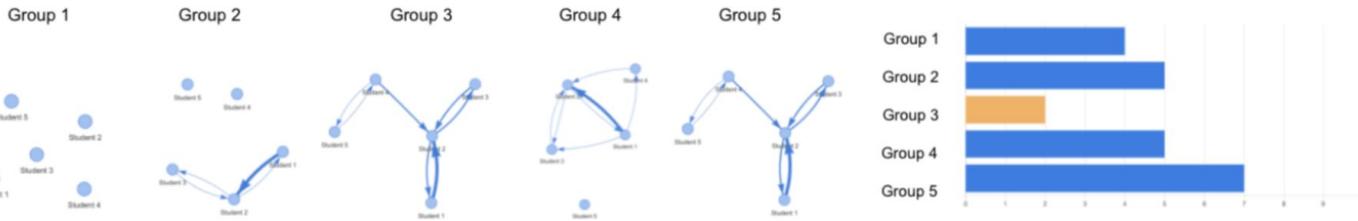
How are groups **progressing** in their Gdocs?



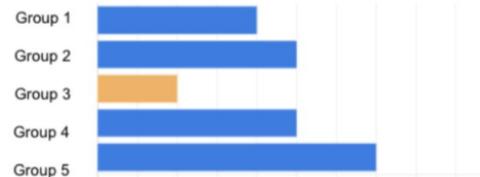
Are there groups that are not **discussing** much?



How are students interacting in Zoom?



In which room have I spent the **least** time?

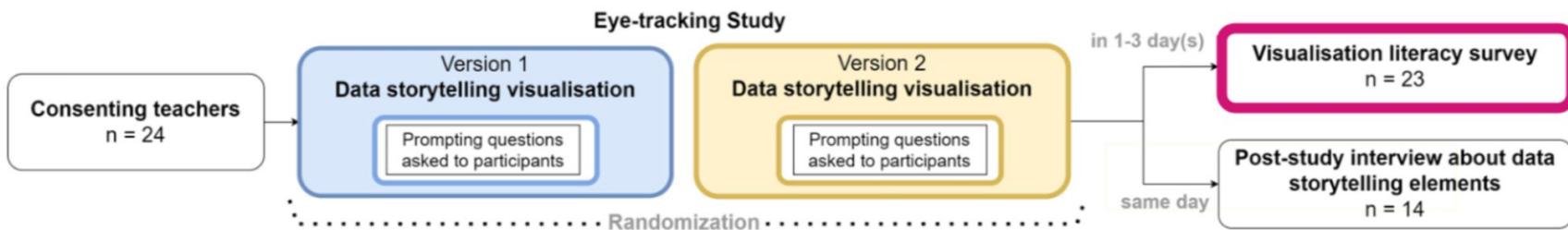


Pozdniakov, Martinez-Maldonado, Tsai, Echeverria, Srivastava, and Gasevic. 2023. **How Do Teachers Use Dashboards Enhanced with Data Storytelling Elements According to their Data Visualisation Literacy Skills?**. In LAK23, March 13–17, 2023, Arlington, TX, USA. ACM, New York, NY, USA,

Previous and current DS-LA work



Dr Stanislav Pozdniakov



Results suggest that **high VL teachers**

- adopted **complex exploratory strategies** and
- were more **sensitive to subtle inconsistencies in the design**;

while **low VL teachers**

- **benefited the most** from more explicit data storytelling guidance
- such as accompanying complex graphs with **narrative** and semantic **colour encoding**

Previous and current DS-LA work

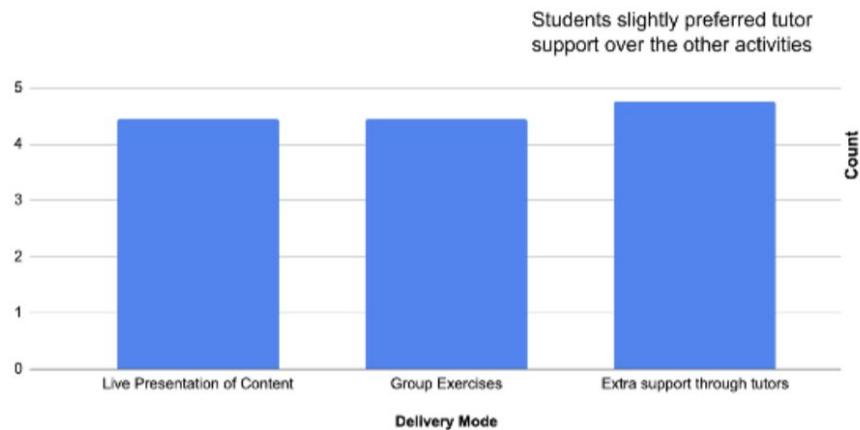


Mikaela Milesi

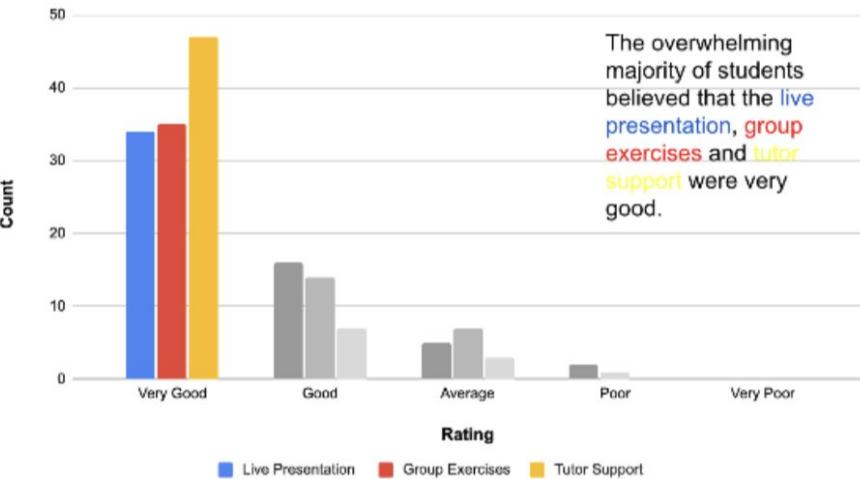
Data Storytelling **prototypes designed by teachers** to study the role of the **data story designer**.....and **potential risks and ethical dilemmas**

What Activities Do Students Prefer?

Ratings Out Of 5 Per Delivery Mode



Programming Bootcamp Student Opinion



Previous and current DS-LA work



Mikaela Milesi

INCIDENTAL RISKS

"it's easy to potentially tell the wrong story or tell a story that is **deviating from something else** that could have been a bigger and truer story"

ETHICAL OBLIGATIONS

Data storytelling features could be "**maliciously [to] hide certain data** or insights from people if they are less flattering"

if designers have "certain personal goals [for] the program ... it's important that they **put that bias aside** and work with a team of different stakeholders in terms of picking which stories to present"

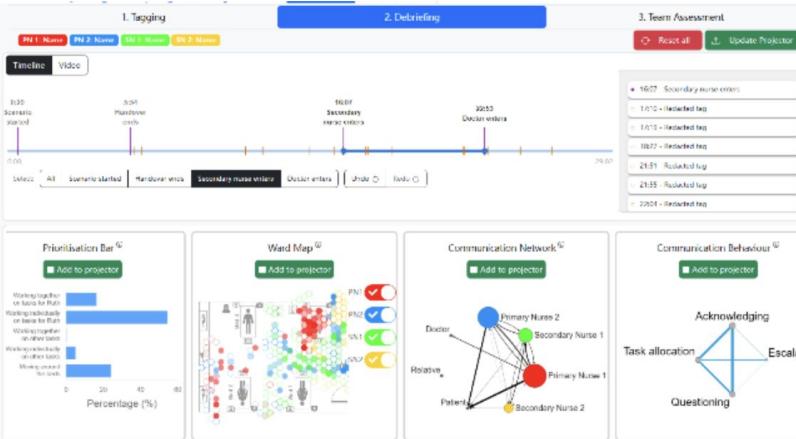
EXPERTISE REQUIRED BY THE DESIGNER

"there is a risk of the storyteller **missing [insights]** ... if they are focusing on a specific story"

MANIPULATIVE POTENTIAL

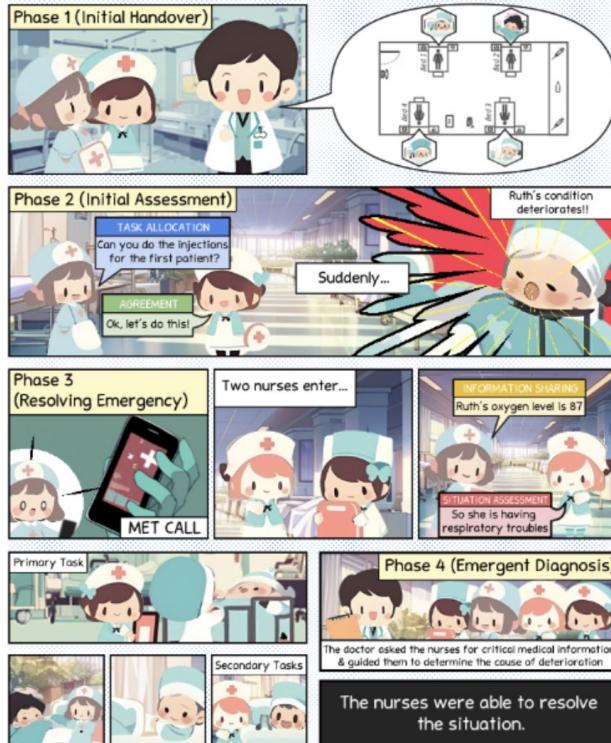
"if my intention right now is to convince somebody that I'm doing a really good job as [a lead educator], [data storytelling] is all I need"

Previous and current DS-LA work



THE LEARNING SCENARIO

METS: Multimodal Learning Analytics of Embodied Teamwork Learning



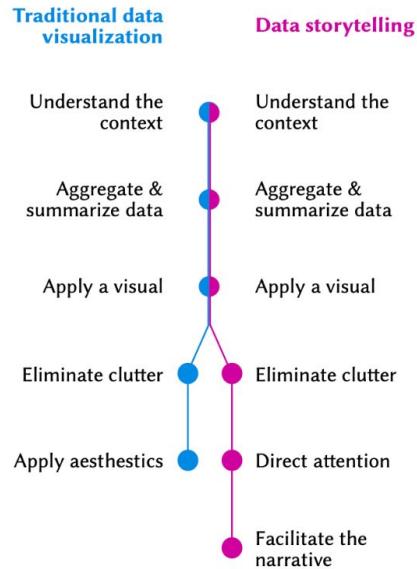
Mikaela Milesi

GenAI-enhanced data comic prototypes created using a combination of the GenAI tool, **Midjourney**, and **graphics illustration software**.

Previous and current DS-LA work

Non LA Data Storytelling work

Previous and current DS-LA work



(a) Principles of DV and DS

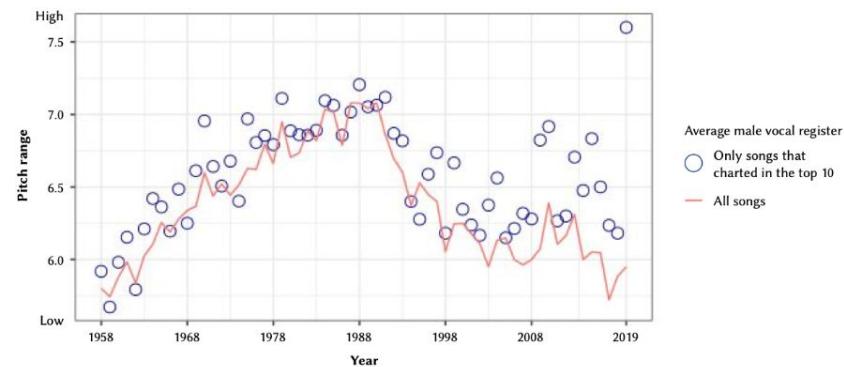
Phases	Principles	Concrete actions
Explore the data	Understand the context Define the audience and the purpose of the visualisation	- Brainstorm & research - Find data
	Aggregate & summarize data Define the main data points to deliver the purpose	- Clean data - Manipulate data if applicable
	Apply a visual Translate data into a visualisation	- Select an appropriate graph type
	Eliminate clutter Reduce the cognitive load	- Apply Gestalt principles - Remove data labels, data markers, grid, legend, tick marks, axis label
	Direct attention Ensure visual guidance for the user	- Remove unnecessary data and push necessary, but non-focal data to the background - Choose preattentive attributes for focal data points e.g. orientation, shape, size, line length, hue, intensity, curvature
	Facilitate the narrative Deliver the message	- Apply narrative text labels to focal data points - Ordering & Interactivity - Clear title delivering the main insight or outcome

(b) Data storytelling framework

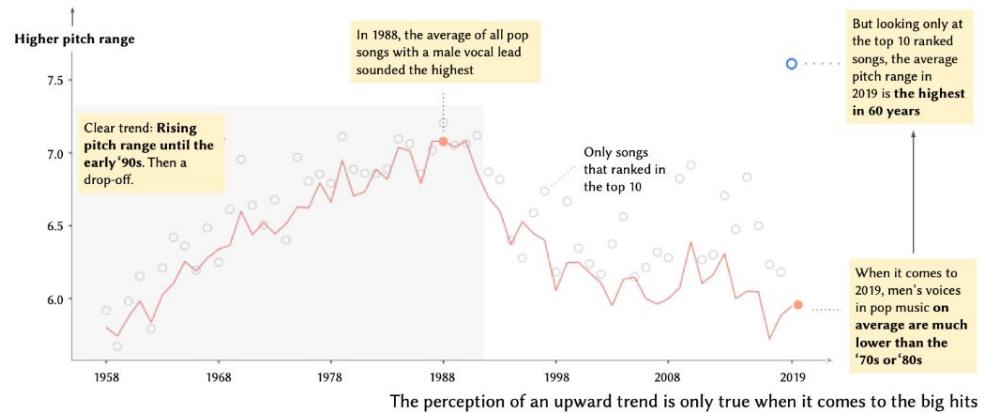
Previous and current DS-LA work

Men's voices in pop music

Development of the average vocal pitch range of songs with a male vocal lead compared to the pitch range of songs that ranked in the top 10 of the Billboard Hot 100 charts



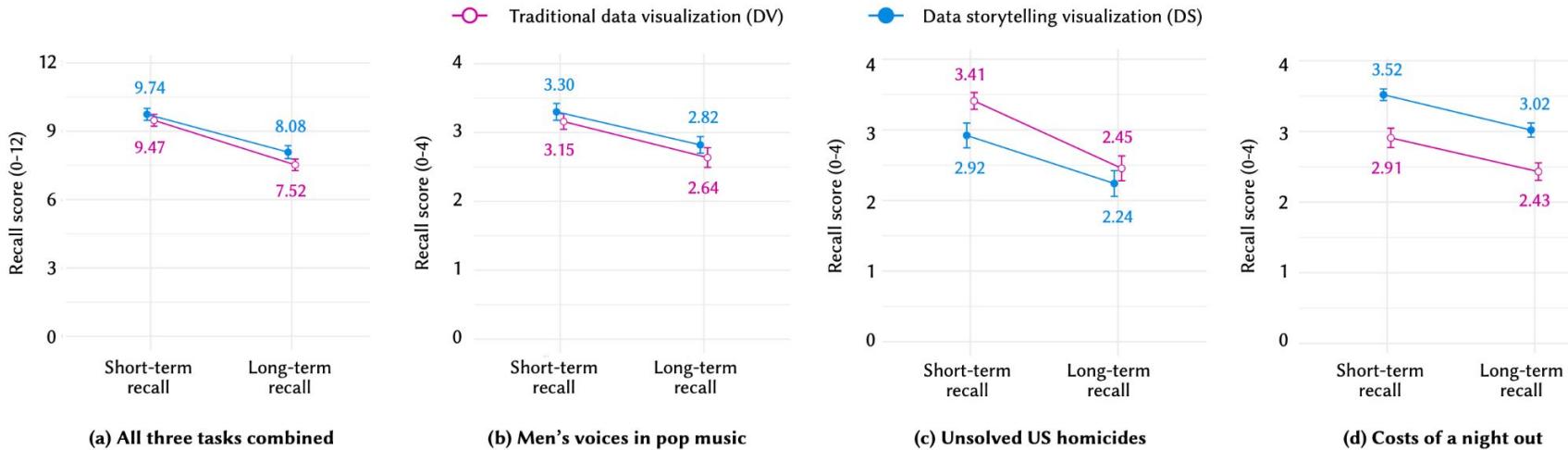
Nowadays it sounds like men in pop music sing **much higher** on average than they used to, but it is **actually the other way around!**



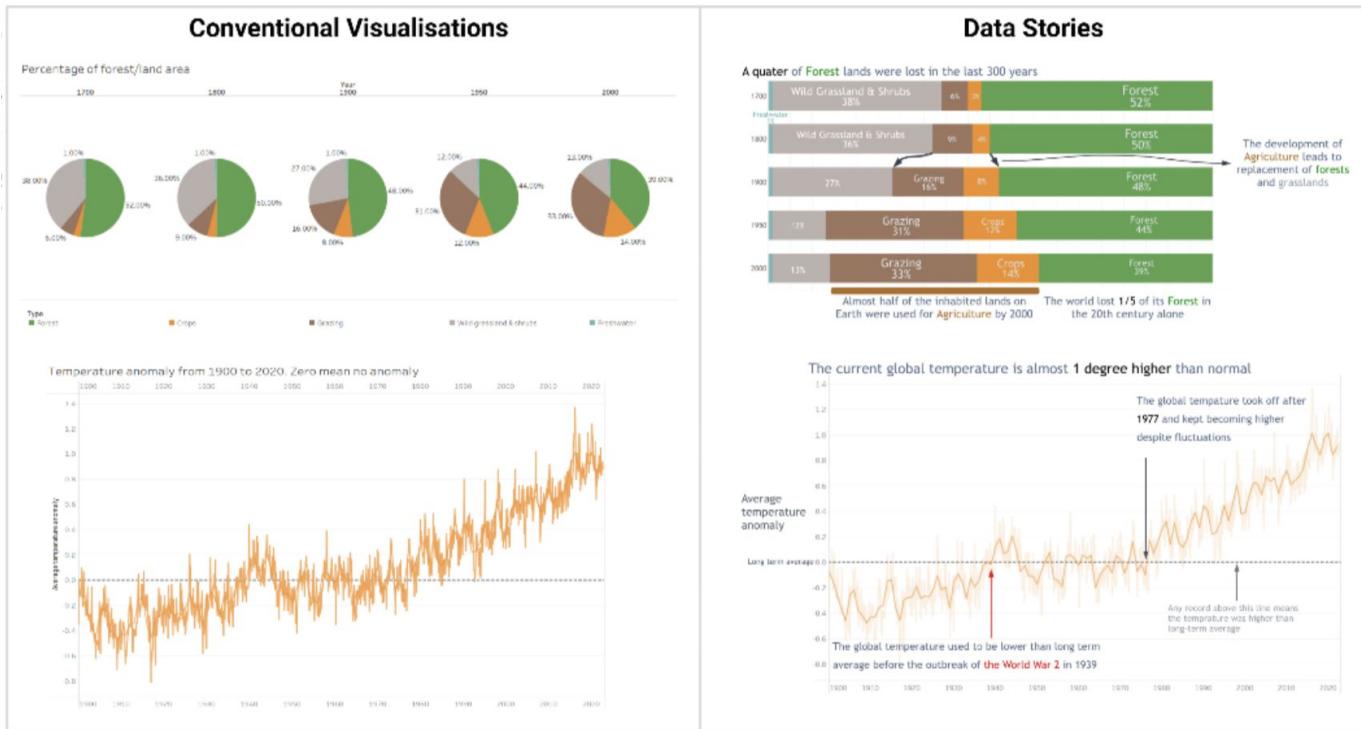
Previous and current DS-LA work

No significant differences in recall between traditional visualisations and data storytelling visualisation.

But ... the **cognitive load** induced **by different chart types and self-assessed** prior knowledge on the chart topics could possibly have a moderating effect on information recall.



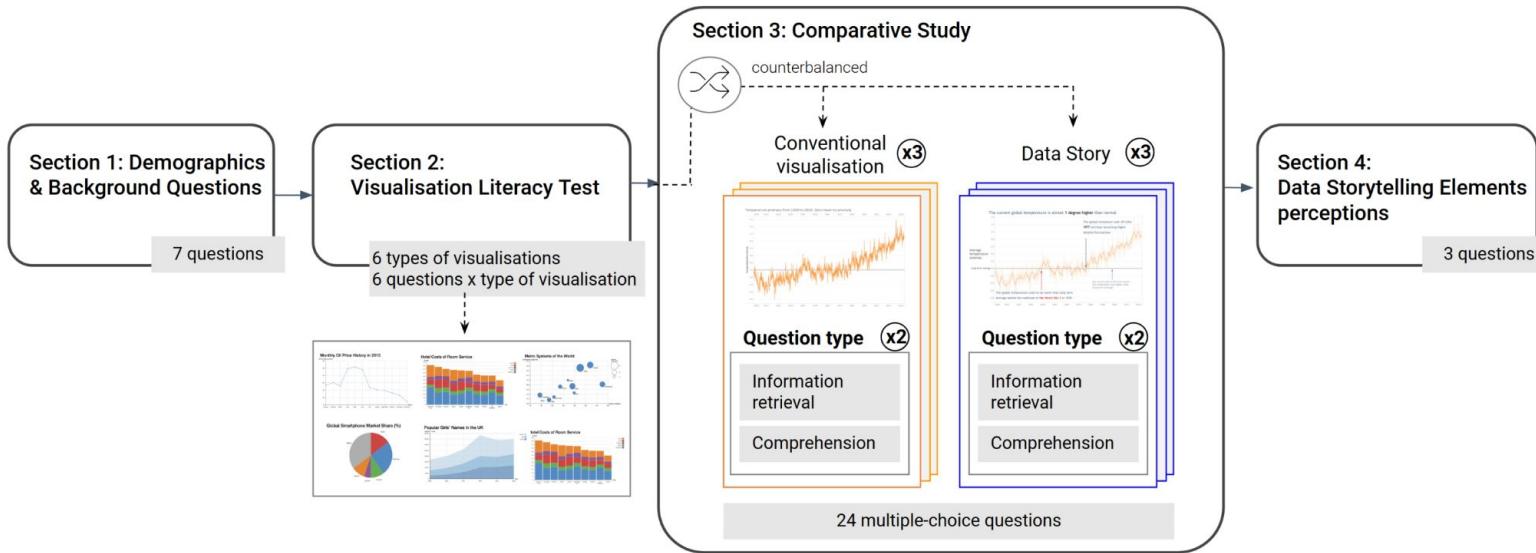
Previous and current DS-LA work



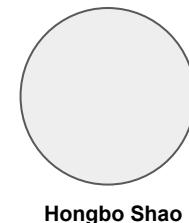
Hongbo Shao

Previous and current DS-LA work

Hongbo Shao



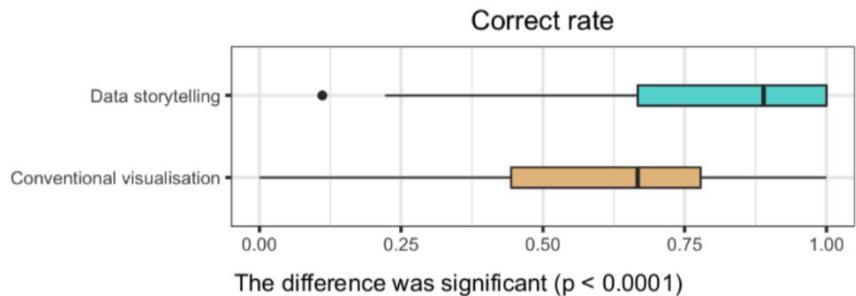
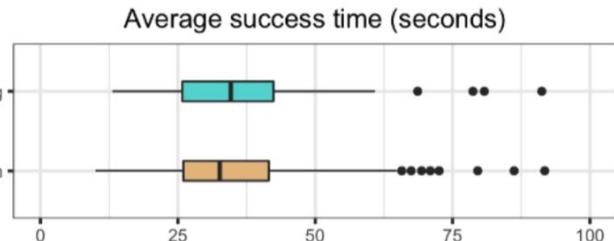
Previous and current DS-LA work



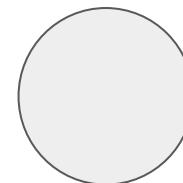
Hongbo Shao

Efficiency

Visualisations **with** Data Storytelling elements **did not** help participants to respond data questions **faster**



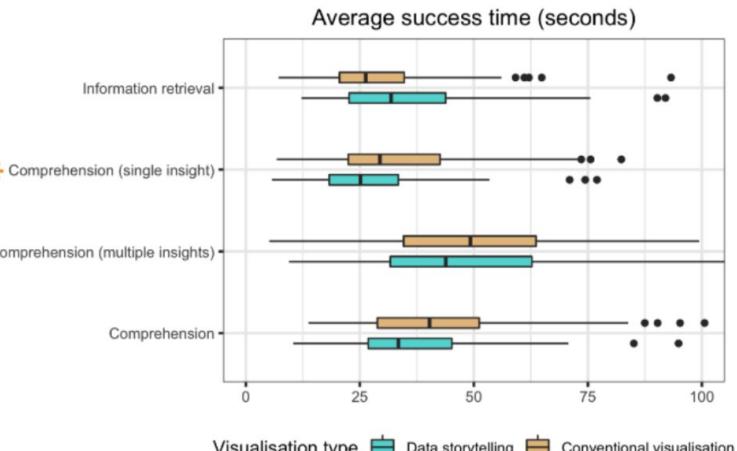
Previous and current DS-LA work



Hongbo Shao

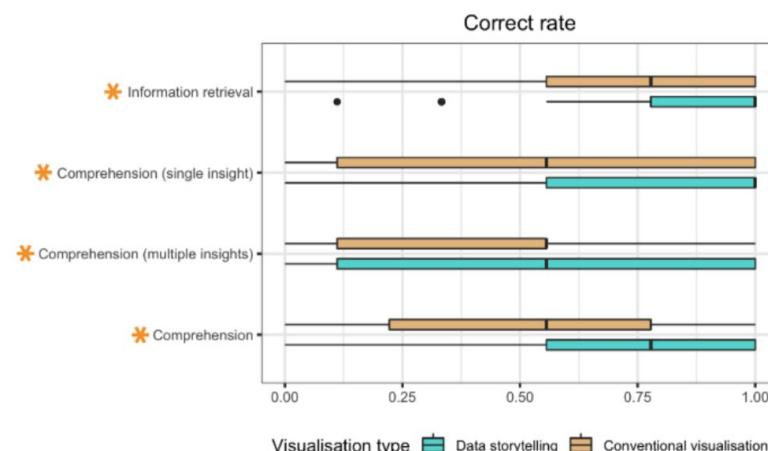
Efficiency

Visualisations **with** Data Storytelling elements **did actually** help participants to respond **simple comprehension questions faster**



Effectiveness

...and **did** help participants to respond ALL TYPES of questions **more accurately**



Previous and current DS-LA work

Data Storytelling as part of the **learning design**

Previous and current DS-LA work



Dr Lujie Karen Chen

“Digital Data Storytelling: is an emerging concept that integrates the data storytelling process of generating data stories and the creative process of digital storytelling to culminate into data stories presented as **short (1-5 min) videos**”

Example: **Hans Rosling’s 4-minute video** that tells the data story of the development trajectory of 200 countries in 200 years (BBC, 2010)

“The use of Digital Storytelling in STEM education has not been fully exploited, and there is a lack of educational projects that articulate learning objectives with a reconstructive orientation the process of reconstructing the meaning of a given concept (Wu & Chen, 2020).”

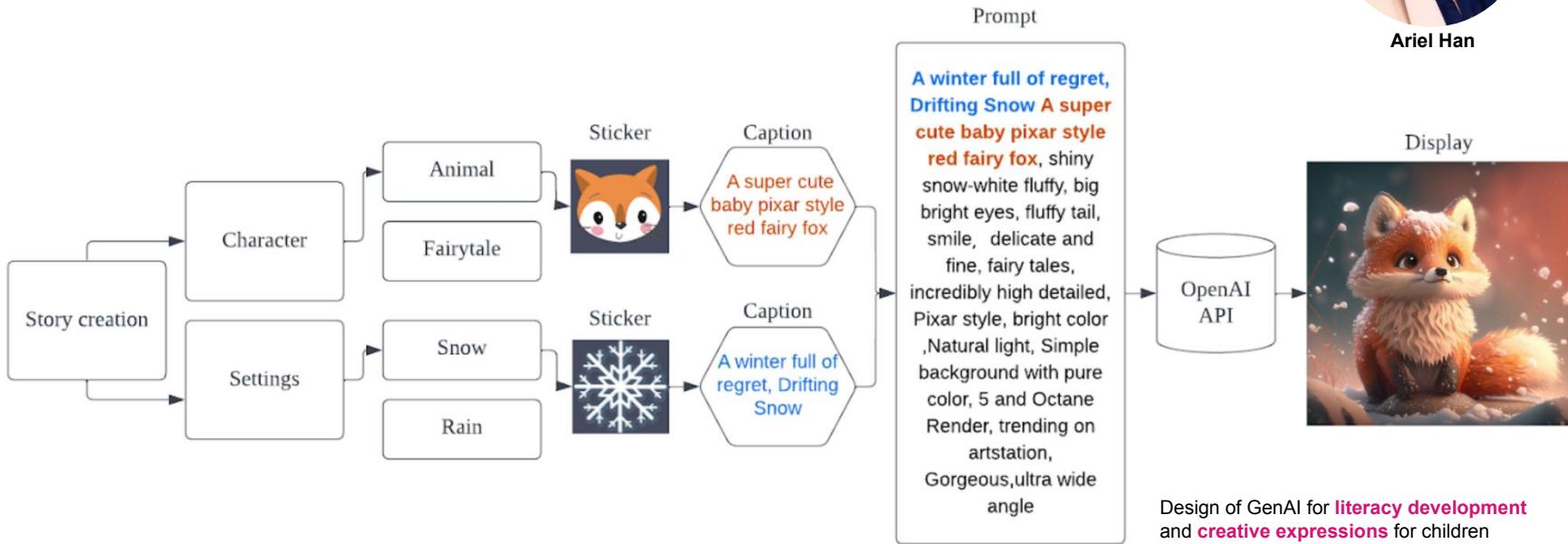
Qualitative results:

“...it [DDS] got me to **think about preparing information to share and the best way to articulate it in a way that is easy to understand and descriptive ...**”

Previous and current DS-LA work



Ariel Han



Design of GenAI for **literacy development** and **creative expressions** for children

Presentations

5 minutes presentation + 5 minutes Q&A



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Presentations

GOAL

To learn about **your Data Storytelling approaches** and understand the **challenges** and **opportunities** you have encountered in your DS in LA research.

Presentations

Data Storytelling for Feedback Analytics

Bhagya Maheshi^{*,†}, Mikaela Elizabeth Milesi[†], Hiruni Palihena[†], Aaron Zheng[†], Roberto Martinez-Maldonado[†] and Yi-Shan Tsai[†]

Monash University, Victoria 3800, Australia

Presentations

YarnSense: Automated Data Storytelling for Multimodal Learning Analytics

Gloria Milena Fernández-Nieto^{1,*}, Vanessa Echeverria^{1,3}, Roberto Martinez-Maldonado¹ and Simon Buckingham Shum²

¹ Monash University

² University of Technology Sydney

³ Escuela Superior Politécnica del Litoral, Guayaquil, Ecuador

Presentations

Data Storytelling on Multi-modal Knowledge Graph via Data Comics: a case study in Yanyuwa Language

Zhiping Liang¹, Zijie Zeng¹, Gloria Fernandez Nieto¹, Yuheng Li¹, Yi-Shan Tsai¹, Guanliang Chen¹, Zachari Swiecki¹, Dragan Gašević¹, John Bradley² and Lele Sha^{1,*}

¹Center for Learning Analytics at Monash (CoLAM), Monash university

²Monash Indigenous Studies Centre, Monash university

Time for coffee



30 minutes



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Presentations

5 minutes presentation + 5 minutes Q&A



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Presentations

Use of SHAP values for identifying differences in behaviors for subpopulations under intervention

Juan A. Talamás-Carvajal^b, Hector G. Ceballos-Cancino^b

a Tecnológico de Monterrey, School of Engineering and Science, Av. Eugenio Garza Sada 2501 Sur, Tecnológico,
64849 Monterrey, N.L, Mexico

b Tecnológico de Monterrey Institute for the Future of Education, Av. Eugenio Garza Sada 2501 Sur, Tecnológico,
64849 Monterrey, N.L, Mexico

Presentations

Automating Data Narratives in Learning Analytics Dashboards using GenAI

Adriano Pinargote^{1,*}, Eddy Calderón¹, Kevin Cevallos¹, Gladys Carrillo¹, Katherine Chiluiza¹ and Vanessa Echeverria^{1,2}

¹ Escuela Superior Politecnica del Litoral , (Information Technology Center), Campus Gustavo Galindo Km. 30.5 Vía Perimetral, P.O. Box 09-01-5863, Guayaquil, Ecuador

² Monash University, Clayton, VIC, Australia

Presentations

From Visualizing to Narrativizing: Powerful Data Storytelling through Non-Player Characters

Maurice A. Boothe Jr.¹, Jeffrey S. Brenneman¹

¹ New York University

Future DS-LA work

Future DS-LA work: Generative AI

LAD with 4 visualisations

A Session 287

1. Tagging 2. Debriefing 3. Team Assessment

Timeline: 0:00 Scenario starts, 6:17 Handover ends, 15:38 Secondary nurse enters, 22:57 Doctor enters.

Prioritisation Bar: Working together on tasks for Ruth (Bed 4), Working together on other tasks, Working individually on other tasks, Moving around the beds.

Ward Map: Shows the spatial distribution of team members (PN, SN, Doctor) across the ward.

Communication Network: Visualizes interactions between team members (Doctor, Primary Nurse 2, Primary Nurse 1, Secondary Nurse 1, Secondary Nurse 2, Patient, Relative).

Communication Behaviour: Categories include Acknowledging, Task allocation, Escalating, Questioning.

Integrating Multiple Visualisations: Did we show the expected behaviours for this stage?

Based on the timeline, this appears to be Stage 3: Secondary nurse enters. The expected behaviors include two students working collaboratively on the medical emergency at Bed 4 and at least one student continuing with tasks at Beds 1 or 2. The bar chart shows significant time spent on tasks for Ruth (Bed 4), both collaboratively and individually, indicating adherence to the expected behaviors for this stage.

Explaining Data Collection and Analysis: What data was used for the bar chart?

The bar chart, labeled as "Prioritisation Bar," used data from the team's spatial behaviors to illustrate their prioritization strategy. It shows the percentage of time spent on various behaviors such as working together on tasks for Ruth (Bed 4), working individually on other tasks, working individually on other tasks, and moving around the beds. This data was likely derived from the positioning data collected during the simulation, as outlined in my knowledge source.

B VisChat clarifies queries, contextualises responses.

Seeking Clarification: Who did I communicate with?

To determine who you communicated with, please provide the name or role you had during the simulation.

Contextualising Response: primary nurse 2

As Primary Nurse 2, you communicated with the doctor, Primary Nurse 1, both Secondary Nurses, and the patients. This is indicated by the lines connecting to your icon in the Communication Network.

Personalised Response: Where did I spend most time?

Primary Nurse 2 spent most time around Bed 4, indicated by the high concentration of blue hexagons in that area of the Ward Map.

C

D

Explains data analysis and collection methods.

Future DS-LA work

When building data stories takes time and effort, some **people may wonder whether AI tools can be used to automate data storytelling.**

... four main reasons why data storytelling can't or shouldn't be fully automated.

1. **Oversimplification of what data storytelling is**
2. **Storytelling is a uniquely human skill**
3. **Transparency and trust are essential to adoption**
4. **Not everything that can be automated should be**



Brent Dykes. [\[Forbes link\]](#)

The Future Of Data Storytelling Is Augmented, Not Automated

Brent Dykes Contributor

I write about how to drive more value with data and analytics.

Follow

Feb 27, 2024, 12:23pm EST



While many are looking at AI automating data storytelling, it's better to view it from how AI and ... [\[+\]](#) ISTOCK | IMAGINIMA

As evidenced by the Palawa oral traditions of the Tasmanian

Future DS-LA work

With the emergence of AI, we now have a **potential partner that can augment how we find and tell stories with data.**

Even though human beings have been developing their storytelling skills over thousands of years, the rapid pace of AI innovation means **we may achieve more with less effort.** Data storytelling is a responsibility we shouldn't mind sharing but also one that humans should never surrender—it's engrained in our DNA and essential to our success.



Brent Dykes. [[Forbes link](#)]

Forbes

The Future Of Data Storytelling Is Augmented, Not Automated

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Future DS-LA work

Discovering insights

Data Storytelling Comparison: Humans vs. AI

	Humans only	AI only	Humans + AI (Augmented)
Data preparation	Time-consuming and error prone as data volumes increase.	Highly efficient and accurate with rule-based approach.	Humans identify relevant data sources and frame the right questions. AI automates cleaning, merging and structuring data for analysis.
Basic data analysis	Aided by software tools to perform simple calculations and make observations. Harder with larger datasets.	Highly efficient at performing simple calculations and analyzing larger datasets.	AI performs initial analyses. Humans interpret the results, identifying meaningful anomalies, trends and patterns.
Advanced data analysis	Requires time, advanced skills and analytics tools. Must understand the business context to find actionable insights.	Spots anomalies, patterns, and trends in complex datasets. Lacks contextual understanding to frame their significance for the business.	AI analyzes and models complex relationships. Humans apply domain knowledge to refine interpretations, models and hypotheses.
Data visualization	Requires some data visualization and design skills. Must understand best practices for explanatory charts.	Relies on pre-defined criteria to determine suitable data visualizations. May not identify the right chart and design for a particular data scene.	AI suggests optimal visualization types and approaches. Humans customize the charts for clarity, context and visual impact.
Narrative creation	Skilled at connecting the dots in the data and using storytelling techniques to build stories. Use innate creativity, empathy and contextual understanding.	Summarizes findings but lacks empathy and contextual understanding to build meaningful narrative.	Humans craft a compelling story. AI offers or suggests enhancements to further enrich the narrative.
Audience alignment	Able to empathize and understand various audiences so content resonates more strongly.	Difficult to tailor content to different audiences without knowing their needs and interests. Empathy and customization are weaknesses.	Humans understand the intended audience's interests and needs. AI helps personalize the content delivery based on audience profiles.



Brent Dykes. [[Forbes link](#)]

Future DS-LA work

Communicate
insights

STORYTELLING STEPS

GENERATE AI

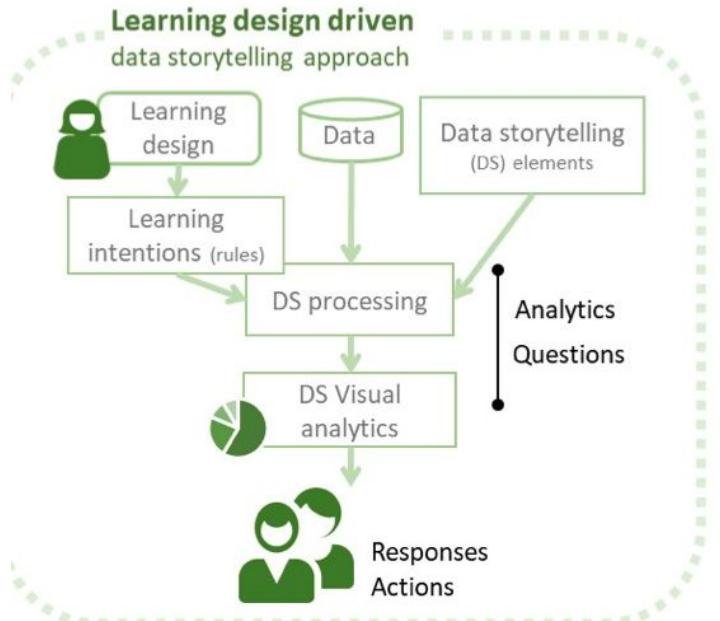
DETERMINE PURPOSE



Help me clarify the purpose of my presentation into one sentence. Our spending is too high and I don't want to do layoffs. I need to speak with my team. What should the focus of my presentation be?



Reflecting the present



How do you position your work in current DS approaches?

What tools, techniques, solutions can be used on each component?

What are the advantages and disadvantages?

What are the benefits and drawbacks of current tools, techniques, solutions?

Group activity

Let's work in groups - 45 mins



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Thinking about the future

What aspects should we focus, as a research group, in future work?

- Generate/ discover insights
- Communicate insights

Thinking about the future

What aspects should we focus, as a research group, in future work?

When discussing on these, consider the following aspects:

- **Human-centredness:** How can we include stakeholders perspectives in these solutions? What is a good story from the LA perspective?
- **Technology:** Are we there yet? What is needed to improve/automate the process of including DS into our LA solutions?
- **FATE:** Does our LAD solution adhere to best practices on **fairness**, **accountability**, **transparency** and **ethics**? Does our LAD solution mitigate bias? Are stories fair?
- **Impact on teaching and learning:** What considerations are needed to measure impact of our LAD solutions? How can we measure this impact? Can we use DS-LA to assess teaching/learning?

<https://bit.ly/DS-LAK-future-ideas>



Final discussion

15 min



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Previous LA work

- LAK paper -> Mikaela Yi-Shan data comics, Gloria, Jimmie [done]
- Echeverria DS elements / Explanatory visualisations [done]
- Maldonado layer approach [done]
- Chen
- Fernandez [done]
- Pozdniakov [done]
- **Karen** [search]
- Not just dashboards -> script for communication, co-design [storyboard] -> engage of students to co-create LA interfaces, to create teaching content for young learners [[link](#)].
- Storytelling - Generative AI: opportunities of using GenAI to create stories

Previous work

Storytelling for educational purposes

Storytelling for explanatory purposes

Storytelling to design for educational purposes

Motivations and foundations

STORYTELLING AS THE OLDEST FORM OF
EDUCATION



Humans have always told stories to pass down cultural beliefs, traditions, and history to future generations.

It's our way of learning and sharing information with each other. In that way, it's the oldest form of education we have.

Motivations and foundations

STORYTELLING AS AN EFFECTIVE FORM OF EDUCATION

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Vol. 64, No. 3, 2018

[Original Article]

Effects of storytelling on the childhood brain : near-infrared spectroscopic comparison with the effects of picture-book reading

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Abstract

In children, storytelling provides many psychological and educational benefits, such as enhanced imagination to help visualize spoken words, improved vocabulary, and more refined communication skills. However, the brain mechanisms underlying the effects of storytelling on children are not clear. In this study, the effects of storytelling on the brains of children were assessed by using near-infrared spectroscopy (NIRS). Results indicated significant decreases of the blood flow in the bilateral prefrontal areas during picture-book reading when the subjects were familiarized in comparison to the cases of the subject naïve to the stories. However, no significant differences in the blood flow were found during storytelling between the subjects naïve and familiarized to the stories. The results indicated more sustained brain activation to storytelling in comparison with picture-book reading, suggesting possible advantages of storytelling as a psychological and educational medium in children.

Key words : Storytelling, Picture-book reading, Children, NIRS

“The results indicated more sustained brain activation to storytelling in comparison with picture-book reading”

“In agreement with the previous clinical claims discussed above, our results may support usefulness of storytelling in education.”

Motivations and foundations

LADs can be difficult to understand by non-data experts

LADs may be not as effective in communicating insights

LADs failed to align with teachers pedagogical intentions

People are familiar with stories, communicating teaching and learning outcomes using data stories is an opportunity for LA field.

DS provide computer-assisted guidance to support casual users, or users with less experience in data analysis, to interpret data visualisations.

Stories emerged from the analysis of data and can be presented by emphasising relevant data points in a way that non-experts are supported to interpret such data.

Motivations and foundations

How do we kickstart the **Data Storytelling process?**

<https://gramener.com/storylabs-publications/defining-data-storytelling>

Motivations and foundations

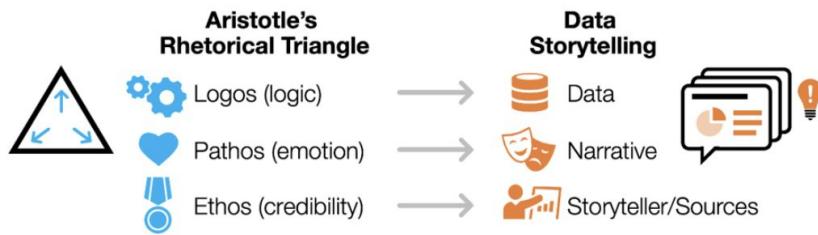
- Guidance can be implemented in visualisations via: 1) visual cues (colour highlights, shapes, annotations). 2) providing different visualisation techniques, 3) or via data storytelling.

DS uses prominent visual features:

- Colour
- Shape
- Capture attention
- Guide interpretation of key information
- Minimise visual clutter to prevent cognitive overload
- Include textual narrative (explain data points, emphasize important sections of the visualisation)

Future DS-LA work

3. Transparency and trust are essential to adoption



Brent Dykes. [\[Forbes link\]](#)

Forbes

The Future Of Data Storytelling Is Augmented, Not Automated

Brent Dykes Contributor ⓘ
I write about how to drive more value with data and analytics.

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Feb 27, 2024, 12:23pm EST

While many are looking at AI automating data storytelling, it's better to view it from how AI and ... [+] ISTOCK | IMAGINIMA

As evidenced by the Palawa oral traditions of the Tasmanian