Exploring the Integration of Data Visualisation Through Self-Quantification: Insights From School Education

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In an era increasingly defined by the proliferation of big data and its transformative impact on decision-making across disciplines, the ability to interpret and engage with complex datasets has become an essential skill for future generations. This literature review reconceptualises data visualisation through the lens of school education and proposes a framework. By framing data visualisation as both a product and a process, the paper explores how data visualisation be utilised in activities framed within the context of self-quantification.

Background

Big data, which has been re-shaping modern lives through the way we think and act, significantly expands the amount of information available for use in various aspects of life, enabling innovative ways through which people engage in data across different fields (Cukier & Mayer-Schoenberger, 2013). One such innovation is the development of wearable devices and mobile apps that track individuals' physical and emotional activities. By collecting and analysing real-time data, these technologies offer valuable insights into health, behaviour, and well-being, illustrating the potential of big data to transform everyday experiences into quantifiable metrics - a process known as *self-quantification* (Maltseva & Lutz, 2018). Self-quantification relies on data visualisation, which enables users to interpret their data, track changes, and make informed decisions through real-time visual displays. From the perspective of mathematics education, this process of self-quantification provides an engaging and authentic context for students to interact with real-time and personal and dynamic data via dynamic data visualisations.

Given the potential of self-quantification and data visualisation to enhance students' engagement with real-world data, integrating data science projects grounded in the context of self-quantification emerges as a valuable endeavour (Lee, 2019). However, integrating innovative data science projects into an already overcrowded curriculum can be challenging for many school educators. One possible reason is that data science draws on content knowledge from multiple disciplines, including mathematics, computer science, and statistics, as well as domain-specific knowledge of different subjects (Donoho, 2017). The interdisciplinary nature of data science makes it complex to be integrated into one single subject area without collaboration between educators from different disciplines (Herro et al., 2022). Additionally, curricula often lack sufficient detail on how data can be effectively visualised as a tool for students to make sense of in data-rich investigations (Australian Curriculum and Reporting Authority [ACARA], 2022; Ministry of Education Singapore [MOE], 2021). This gap in curricular guidance contributes to challenges in equipping teachers with the necessary skills and confidence to integrate data visualisation into their teaching practices. A recent study on over 3,000 primary and secondary teachers' perceptions of teaching data science indicate that many teachers do not feel confident in using data visualisation as a tool to support students' learning due to their lack of content knowledge and experience in data science (Filderman et al., 2022). To begin to address the problems discussed above, this paper aims to investigate following research questions:

RQ1 – How has the literature defined data visualisation relevant to school education?

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RQ2 - How can data visualisation be utilised in activities framed within the context of self-quantification?

The paper is structured in two main parts. The first part presents a literature review that explores data visualisation within the context of school mathematics curriculum, with a particular focus on how it connects individuals to the broader world via self-quantification. The second part provides a simple example of how data visualisation can be used a tool to facilitate students' exploration of data within the context of self-quantification.

Literature Review

Given the exploratory nature of the research question, a narrative literature review was conducted to synthesise existing research and theoretical perspectives on data visualisation, self-quantification, and their applications in mathematics education. The first section of the literature review examines the concept of data visualisation and presents a conceptual framework of data visualisation, and the second section uses the framework to explore the application of data visualisation in various forms of self-quantification.

Data Visualisation within the Context of School Mathematics Curriculum

In mathematics education, visualisation acts as both a *product* and a *process* that facilitates understanding (Arcavi, 2003). As a subset of mathematical visualisation, data visualisation embodies these dual roles, serving as both a *product* (e.g., a visual representation of data) and as a *process* (e.g., a process of reasoning with data). Beyond its role in mathematics, data visualisation is an essential component in data science, where it enables the exploration, analysis, and communication of data (Donoho, 2017). As mentioned in the Background, the concept of data visualisation is not explicitly illustrated in curricula. For example, the Australian Curriculum Version 9.0 mentions the visualisation of data through presenting it in summarised forms; however, this description remains insufficiently comprehensive to fully capture the scope and depth of data visualisation as a tool for analysis, exploration, and interpretation of data. To address this gap, we explore the concept of data visualisation in its role as both a product and a process.

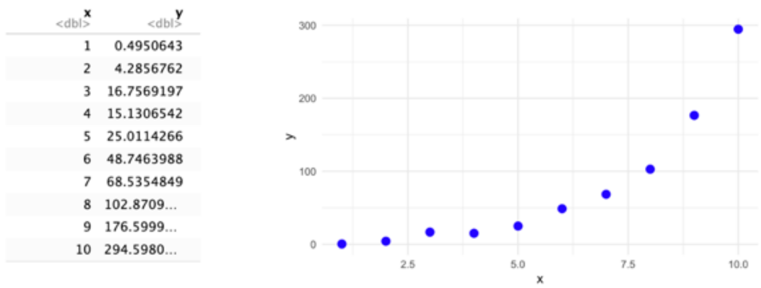
Data Visualisation Acting as a Product

As a product, data visualisation transcends the role of a graph into a data graphic. A mathematical graph is an abstraction of observations or thoughts about the world (Wilkinson et al., 1999). *Data graphics* are broader, including visual representations of information, data, or knowledge designed to communicate complex relationships or patterns clearly, efficiently, and aesthetically (Tufte, 2001). That is, a visual representation is carefully designed and accomplished by *aesthetic attributes* such as frameworks (e.g., axes), visual dimensions (e.g., the lines on a line graph), labels (e.g., title and keys), and backgrounds (e.g., colouring and grids) (Friel et al., 2001). These attributes enable data graphics to *reveal* and *communicate* complex information, transforming abstract data into visually interpretable forms that enhance understanding and insights (Tufte, 2001). The use of these aesthetic attributes may vary depending on the purpose of the data graphic within a data-rich investigation. For instance, when a data graphic is generated for presentation purpose (i.e., presentation data graphics), significant focus is placed on its aesthetic attributes, as these are critical for effectively displaying and explaining the information conveyed by the data (Unwin, 2020). If aesthetic attributes are not used appropriately, the data graphic may fail to aid in understanding the data or even mislead by obscuring or distorting the intended message. Misleading visual representations are commonly found not only among novices creating data graphics but also in media, where intentional or unintentional distortions can (mis)shape perceptions of the data. To date, much of the work in data graphics has focused primarily on presenting information, with less attention given to what can be inferred or deducted from it (Chen et al., 2008; Hudson et al., 2024). Within primary and secondary mathematics education, the appropriate application of aesthetic attributes remains an underexplored and insufficiently addressed aspect.

In addition to creating presentation-focused data graphics, data scientists frequently examine existing datasets from various perspectives, rapidly generating multiple exploratory data graphics to uncover new insights (Unwin, 2020). Compared to presentation data graphics, which are typically created for audiences not directly involved in the data investigation, exploratory graphics are primarily intended for use by data scientists themselves. As a result, less emphasis is placed on refining aesthetic attributes, with more time and effort dedicated to generating graphics that reveal hidden patterns in the data from various perspectives. For example, the scatter plot in Figure 1 reveals the exponential pattern of the dataset, a feature that is not immediately apparent in its tabular form. This use of exploratory data graphics as a tool also highlights and links to another key feature of data visualisation - its role as a *process* for exploration and analysis of data.

Figure 1

The Use of Exploratory Graphics to Reveal the Pattern of Dataset



x <dbl>	y <dbl>
1	0.4950643
2	4.2856762
3	16.7569197
4	15.1306542
5	25.0114266
6	48.7463988
7	68.5354849
8	102.8709...
9	176.5999...
10	294.5980...

Data Visualisation Acting as a Process

Data visualisation is a powerful *process* that allows us to interpret and represent what data appear to convey (Tukey, 1977). In data-rich investigations, the approach used to explore and analyse data extends beyond using data solely as evidence to confirm a hypothesis – a method known as *confirmatory data analysis*. Instead, these investigations often begin with *exploratory data analysis* (EDA), which encourages delving deeper into data and data graphics to uncover new insights. The notion of delving deeper goes beyond identifying patterns and outliers within a dataset. Data visualisation as a process invites us to ask a critical question: what exactly are we visualising? Although data may appear to be the most obvious answer, a cursory examination of data limits our ability to uncover deeper and more nuanced insights. Within the context of classroom teaching and learning, students are seldom given opportunities to critically engage with the process of generating and wrangling with data (Rubin, 2021). Instead, they often work with pre-prepared, neatly organised datasets that lack the complexity and messiness of real-world data (Gould et al., 2017). To address this gap, learning activities are needed that enable students to actively collect, prepare, and analyse data for exploratory data analysis. By engaging in the entire data lifecycle - from data generation and collection to cleaning, organising, and visualising - students can develop a deeper understanding of the complexities inherent in real-world data (van Borkulo et al., 2023).

Advancements in data science and technology have made innovative *data graphics* increasingly being used in the process of data visualisation. Examples include, but are not limited to, heat maps, dynamic bubble charts, and decision trees. Innovative data graphics expand the possibilities of what can be visualised in exploratory data analysis. For example, a decision tree is more than just a visual display of a dataset; it serves as an algorithm of the reasoning process involved in modelling with the dataset (Erickson & Engel, 2023). In other words, data visualisation not only shows trends and patterns of data but also reveals *information* which might be deduced from data (Chen et al., 2008). The view of data visualisation as a process reflects how data scientists deal with big data, using visualisation to explore the complexity of datasets and then create algorithms for machine learning models (Godsey, 2017). For instance, data scientists often rely on visual tools to identify patterns, test hypotheses, and refine predictive models, making data visualisation an integral part of the iterative process of data analysis and model building. However, this dynamic and process-oriented view of data visualisation is not sufficiently emphasised in the school curriculum, where data visualisation is often reduced to static representations of numerical or categorical data (Lim et al., 2023). Students are rarely exposed to the idea that data visualisation can serve as a bridge between raw data and actionable insights, nor are they encouraged to explore how visualisation tools can be used to develop algorithms or predictive models.

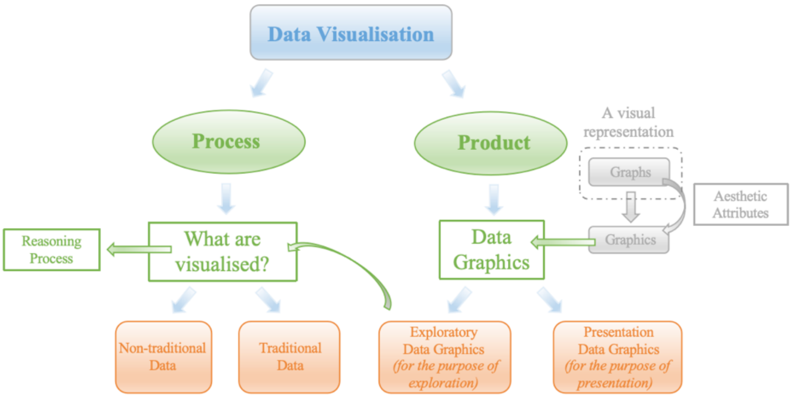
Data and Data Visualisation in School Education

Big data differ from traditional data in three keyways: *volume* (the large size of datasets), *velocity* (the rapid speed at which data are generated and processed), or *variety* (the wide range of data types) (Laney, 2001; McAfee & Brynjolfsson, 2012). Within the context of school education, a dataset may be classified as non-traditional if it demonstrates any of these three defining characteristics. Researchers have underscored the significance of integrating non-traditional data into school curricula to improve students' ability to reason with these emerging forms of data (Noll et al., 2023). Recent research on the use of technology-based data visualisation tools, such as CODAP, has demonstrated the possibility of engaging primary and secondary students in the exploration of large datasets (referred to as *volume*) (Hudson et al., 2024; Zapata-Cardona, 2023). Compared with traditional data such as numerical and categorical data, non-traditional data take diverse and unstructured forms (referred to as *variety*) such as sound, images, text, and other multimedia representations (Arnold et al., 2021). Newer forms of data are generally analysed using advanced technology such as Natural Language Processing for text and Computer Vision images and other multimedia representations. While teaching students these technologies to translate text or image data may not be feasible, it is highly possible to introduce diverse data forms and related creative visualisations (Fergusson & Pfannkuch, 2024). Furthermore, the final characteristic of non-traditional data—velocity—can also be integrated into school education. For instance, a recent study illustrated how students utilised data visualisation tools to examine and analyse real-time temperature data collected by sensors installed within the vicinity of their school community (Fleischer et al., 2022).

The rise of big data has enabled the transformation of many previously unquantifiable aspects of the world into data - a process known as *datafication* (Cukier & Mayer-Schoenberger, 2013). An example of datafication is the use of facial expression data to analyse emotions. Advanced algorithms can capture, quantify, and interpret various facial features, such as the curve of a smile, the furrowing of eyebrows, or the widening of eyes (Martinez & Du, 2012). These features are then analysed to determine emotional states like happiness, surprise, or frustration. By translating these subtle physical cues into data points - such as the distance between the eyebrows and the mouth baseline - this process turns complex human emotions into measurable information that computers can interpret. To achieve this, experts must first identify the *features* (c.f. feature engineering) which refer to any values that can be computed from data for the purpose of modelling the problem (Duboue, 2020). Capturing such features requires individuals to *be aware of*, and able to visualise, the existence of data in real-world, often messy, scenarios. A recent study on data awareness reveals that even students without formal statistical backgrounds can identify potential variables within real-world phenomena, despite not always being explicitly aware of the existence of data (Sherwood & Makar, 2024). To facilitate this process, *engaging and accessible contexts* are needed for students, ensuring that these contexts promote datafication as well as encouraging the exploration of non-traditional data through the incorporation of data visualisation. For instance, self-quantification serves as an exemplary context, as it naturally integrates these elements while fostering student interest. In this section, we have explored the concept of data visualisation and data within the context of K-12 mathematics education, drawing on a review of relevant literature. To consolidate our findings, a framework for data visualisation is presented in Figure 2.

Figure 2

A Framework of Data Visualisation



Data Visualisation in Self-Quantification

A key challenge for many mathematics educators lies in identifying effective strategies to integrate this comprehensive and innovative view of data visualisation into classroom instruction. To address this challenge, we draw upon the concepts on data and data visualisation included in the framework (Figure 2) and explore the role that data visualisation plays in different types of self-quantification – plugged or unplugged.

Self-quantification is a process that involves personally collecting and interpreting data about various aspects of one's own life (Maltseva & Lutz, 2018). The primary advantage of using digital devices for self-quantification is their ability to transform personal data into visual displays in real-time, providing users with immediate insights (Lupton, 2013). These visual displays exemplify the concept of *data graphics for both presentation and exploration*, as outlined in the framework presented in Figure 2. For instance, an individual might establish daily physical exercise goals using a smartphone application. At 3:00 PM, they could review real-time data graphics displaying metrics such as energy consumption and steps taken, interpret the visualised information, and make informed decisions about their activities for the remainder of the day. In this example, real-time data graphics, which are initially designed for presenting information about individuals' physical activity, serve as a medium for communicating insights derived from the data. This process highlights how self-quantification tools not only generate *data graphics for presentation* but also facilitate immediate, actionable insights through the *process* of data visualisation.

Due to advancements in self-tracking technology, such as smartphones and smartwatches, self-quantification has emerged as a new field of research. Self-tracking can also be conducted without the use of technology, as individuals may engage in manual methods of recording and reflecting on their own experiences. For instance, data creatives Lupi and Posavec undertook a one-year self-quantification project, during which they exchanged hand-drawn data visualisations on a specific topic each week (Lupi et al., 2016). In unplugged approaches to self-tracking, individuals must thoughtfully identify and define the *features* that can be quantified to effectively capture data relating to the chosen aspects of one's life. With the abundance of non-traditional data available today, teaching students how to *recognise* and *identify* features of non-traditional data becomes crucial in school mathematics education.

Whether plugged or unplugged, self-quantification offers valuable contexts for designing meaningful, data-rich projects. Wearable technologies empower learners to gather real-time data and interpret dynamic visualisations, gaining insights into their physical, mental, and emotional selves (Wilson, 2012). Over the past decade, researchers have explored the use of self-tracking devices to engage students in collecting and analysing data about their own lives (Lee et al., 2021). Findings from these studies indicate that incorporating real-life and real-time data enhances students' statistical reasoning and deepens their understanding of key concepts in statistics (Lee, 2019). Unplugged self-quantification complements plugged approaches by offering learners more opportunities to transform real-life topics into measurable features and manually create different types of data graphics to effectively explore and present these features. A study focusing on data visualisation found that when given a research topic, students were able to quantify it by identifying and measuring features from their own life (Krekhov et al., 2019). However, these students used data visualisation as a tool for passively representing data (data graphics for presentation), rather than actively using it as a process for exploration and analysis (data graphics for exploration). One possible explanation is that schools often teach data visualisation primarily as *data graphics* to display data, and current mathematics curricula place less emphasis on its role as *data graphics for exploration*. This highlights that incorporating real-life contexts alone does not always result in rich learning experiences with data (MacGillivray, 2023). Instead, designing meaningful learning activities that engage students with authentic contexts and complex data requires careful planning and significant time investment. Consequently, it is essential to provide K-12 mathematics educators with a greater number of guidelines and illustrative examples to facilitate their implementation, experimentation, and provision of constructive feedback to learners.

A Simple Example of Incorporating Data Visualisation

In this section, we demonstrate a simple example to explore the question: *How can data visualisation be utilised in activities framed within the context of self-quantification.* The design of a simple example was informed by insights and theoretical perspectives derived from the literature review.

In this learning activity, students identify, collect, explore, analyse, and present data from their own life to answer the following question: "How do I connect to people surrounding me?". First, students quantify the research question by brainstorming possible measurable features as variables (Van Dijck, 2014). Next, they plan for data collection via *self-tracking* by creating a data journal to document the process, addressing who, how, when, where, and why they connect to family members, friends etc. (Rubin, 2021). During data collection, they gather data on the identified variables over 1 to 2 weeks, using appropriate *data graphics* to organise the data. When organising the data, students use *data visualisation as a process* to note issues like missing data or outliers and adjusting their approach for the remaining collection period. Afterward, they analyse the data at an individual level, identifying patterns and variations while considering the context. They then expand their analysis to the class level, comparing their findings with peers and selecting appropriate statistics for interpretation. Finally, they present and reflect on their findings by creating an infographic (*data visualisation as a product*), evaluating how self-tracking has impacted their lives and ensuring the data graphic effectively communicates their understanding of non-traditional data with *variety* and *velocity*.

The purpose of this sequence of learning tasks is to offer K-12 mathematics educators a practical approach to integrating key elements of data science into their regular teaching practices. The question "How do I connect to people surrounding me?" is intentionally open-ended and uncertain, offering students the opportunity to draw on their everyday experiences to identify measurable features of a phenomenon, which can then be conceptualised and analysed as data within the context of self-quantification (Lee, 2021). The focus on data preparation aligns with the concept of "data-ing," which refers to the process of enhancing data quality, organising it, selecting relevant features, and visualising it effectively to prepare for analysis (Gafny et al., 2024). This learning activity is designed to emphasise the dual role data visualisation plays (as both *a process* and *a product*) at various stages of a data-rich investigation. While the sequence of learning tasks offers educators an idea for designing projects that incorporate non-traditional data, successful implementation of the learning activity hinges on effective teaching practices.

Conclusion

Big data continues to shape various aspects of our daily lives, yet research in the field of data science education is still in its early stages (Gafny et al., 2024). Given the novelty of this research area, it is crucial to explore the practical applications of key data science elements. This paper reinforces potential of data visualisation in primary and secondary mathematics by framing it as both a product and a process. Moreover, we proposed a framework of data visualisation through the lens of school education. However, challenges such as working with messy, real-world data and the interdisciplinary nature of data science underscore the need for thoughtful curriculum design and targeted professional development for educators. To address these challenges, we employed the data visualisation framework as a guiding structure to review literature on self-quantification, which serves as an authentic context for enabling students to explore non-traditional data through data visualisation. Future research should focus on the implementation of this learning activity to investigate the affordances and constraints relating to how students engage in self-quantification through using data visualisation as a tool.

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