Designing business analytics (BA) platforms: tracing the visual redesign process of a startup's BA platform

Anastasia Griva

Lero—The Science Foundation Ireland Research Centre for Software, J.E. Cairnes School of Business and Economics, University of Galway, Galway, Ireland, and

Angeliki Karagiannaki

Department of Management Science and Technology, ELTRUN, The E-Business Research Center, Athens University of Economics and Business, Athens, Greece

Abstract

Purpose – Designing effective business analytics (BA) platforms that visualise data, provide deep insights and support data-driven decision-making is a challenging task. Understanding the elements shaping BA platform design is crucial for success. The purpose of this study is to explore the impact of visualisation on usability (UI) and user experience (UX) while emphasising the importance of insights understanding in BA platform design.

Design/methodology/approach – This paper presents a case study following a startup's journey as it undergoes two redesign phases for its BA platform. A combination of quantitative and qualitative methods is used to assess UX/UI and insights understanding of the platform. Indicatively this included semi-structured interviews, observations, think-aloud techniques and surveys to monitor runtime per task, number of errors, users' emotions and users' understanding.

Findings – Our findings suggest that modifications in aesthetics and information visualisation positively influence overall usability, UX, and understanding of platform insights – a critical aspect for the success of the startup.

Research limitations/implications – Our goal is not to make a methodological contribution, but to illustrate how companies, constrained by time and pressure, navigate platform changes without meticulous design and provide learnings on important elements while designing BA platforms.

Practical implications – This paper concludes with suggested methods for assessing BA platforms and recommends practical practices to follow. These practices include recommendations on important elements for BA platform users, such as navigation and interactivity, user control and personalisation, visual consistency and effective visualisation.

Originality/value – This study contributes to practice as it presents a real-life case and offers valuable insights for practitioners.

Keywords Visualisation, Business analytics, Usability (UI), User experience (UX), Start-ups

Paper type Research paper

1. Introduction

Business analytics (BA) has appeared as a key subject of study for both practitioners and researchers, revealing the importance of data-related problems to be addressed in incumbent

firms (Delen and Zolbanin, 2018). Due to the vast amount of data gathered, plentiful BA platforms have been developed to analyse these datasets, providing in-depth insights and supporting data-driven decision-making (Griva *et al.*, 2018; Li *et al.*, 2022; Raman *et al.*, 2019; Raman *et al.*, 2024; Raza *et al.*, 2023; Tipu and Fantazy, 2023).

When designing BA platforms, a significant challenge lies in effectively visualising these insights to make them attainable to people, while ensuring a seamless platform experience (Franconeri *et al.*, 2021; Vázquez-Ingelmo *et al.*, 2024). Regarding the visualisation, the challenge is to convey information in a way that resonates with diverse end-users, taking into account their different backgrounds and knowledge (Vázquez-Ingelmo *et al.*, 2024), and in a way that facilitates comparisons and benchmarking, allowing businesses to identify areas for improvement and drive enhancements (Agrahari and Srivastava, 2019). To address this challenge, academic effort has been structured mainly around "visual aesthetics" and "information visualisation" that deal with efficient data representation (Banissi *et al.*, 2014; Luo, 2019; Sorapure, 2019). However, apart from the recent study of Vázquez-Ingelmo *et al.* (2024), little research has been conducted to evaluate these elements within BA platforms.

Regarding the need for a seamless platform experience, there is a growing body of literature suggesting models, principles and rules to evaluate usability and user experience in platforms (e.g., Mazumder and Das, 2014) or using them (e.g. Lavie and Tractinsky, 2004; Mazumder and Das, 2014). However, there is only a small subset of literature that focuses on evaluating these elements specifically in BA platforms (e.g., Pohl *et al.*, 2012).

The goal of this study is to examine the impact of visualisation on the usability (UI), user experience (UX) and understanding of insights for a BA platform. To address this objective, empirical evidence is provided by observing the evolution of a retail analytics platform in two phases, reflecting the journey of an early-stage startup.

Early-stage start-ups are often constrained by time and resources, which limits their ability to meticulously design products to enter the market (Karpinskaia, 2023). Instead, they often rely on trial and error, employing quick and pragmatic solutions (Zamani *et al.*, 2022). They translate these failures into growth strategies (Corvello *et al.*, 2024), sometimes without adhering to academic rigour. Nevertheless, these practices can yield valuable insights for practitioners, aligning with or enriching academic knowledge. In this vein, our results indicated that improvements in visualisation can impact positively the usability and the UX of the BA platform. Also, they can have affect significantly the insights understanding. In this context, it is essential to emphasise that our objective is not to present a methodological contribution, acknowledging that the steps undertaken by the startup in redesigning their BA platform may not adhere to best practices. However, our aim is to provide to practitioners (e.g., startuppers) practical knowledge on what they should test and how to do so, and on which elements they should pay attention to when designing their BA platforms.

The remainder of the paper is organised as follows. Section 2 offers a justification for the relevance of this work by discussing visualisation and its importance on insights understanding. This section also examines common evaluation methods for usability and user experience based on existing literature. Section 3 describes an overview of the empirical context. Section 4 presents the findings derived from the visual alterations, while Section 5 provides concluding remarks, practical learnings, along with some limitations and implications for future research, while section 6 concludes the paper.

2. Background

Data visualisation can significantly influence the usability, user experience, and insights understanding, thereby impacting the overall acceptance of a platform (Thüring and Mahlke, 2007; Tuch *et al.*, 2012; Vázquez-Ingelmo *et al.*, 2024). This section introduces visualisation and its significance, followed by an exploration of insights understanding and an overview

on how literature evaluates this aspect. Subsequently, we delve into usability and UX elements, presenting commonly utilised evaluation methods.

2.1 Visualisation

Information visualisation (infovis) is "*the use of computer supported, interactive, visual representations of abstract data to amplify cognition*" (Card *et al.*, 1999). Infovis traditionally was designed for expert users (Sorapure, 2019). However, BA platforms and dashboards might have both experienced and inexperienced users; thus, this is an important challenge. Various researchers highlight the need to make infovis attainable to non-expert audiences, coining terms such as "*communication-minded visualisation*"(Viégas and Wattenberg, 2006), "*utilitarian visualisation*"(Sorapure, 2019), "*casual visualisation*" etc (Pousman *et al.*, 2007). All in all, infovis is an important element in dashboard design (Franconeri *et al.*, 2021; Vázquez-Ingelmo *et al.*, 2024), since wrong visuals can lead to biases, and poor decision-making.

Infovis combines three aspects: visual features (e.g., position, colour and size), textual elements (e.g., labels, instructions and descriptions) and interactive options (e.g., search, filtering and zoom) (Sorapure, 2019). When designing a dashboard, all these aesthetic factors matter. The colours, the position and size of the text, the order and the type of graphs can affect users (Franconeri *et al.*, 2021). Aesthetics is a subjective and multidimensional element that may be interpreted variably depending on an individual's perceptions, background, culture, etc (Miniukovich and De Angeli, 2015; Vázquez-Ingelmo *et al.*, 2024).

2.1.1 Visualisation and insights understanding. When interacting with a BA dashboard, users should be able to fully focus on their tasks without being distracted by overly technical or complex user interfaces (Pohl *et al.*, 2012). In this scenario, aesthetics play an important role in assisting users to understand the visualised information, spot patterns and extract insights (Sorapure, 2019). Effective data visualisation portrays the story-telling behind the visuals (Mei *et al.*, 2020), inspires the end-user and helps then understand complex datasets and structures (Basole *et al.*, 2019). Researchers suggest that creativity and innovation in visualisation is an important prerequisite for understanding the visualised information and generating novel insights (Adagha *et al.*, 2017; Chouki *et al.*, 2023). Infovis plays a crucial role in turning raw information into actionable insights. Preventing errors and ensuring accurate insights comprehension from the visuals are crucial for the decision-making quality in BA platforms (Adagha *et al.*, 2017; Li *et al.*, 2022).

In the literature, various principles are employed to assess visualisation and insight understanding. For instance, some researchers (e.g., Bhandari *et al.*, 2019; Lavie and Tractinsky, 2004) distinguish visual factors into expressive and classical design factors. The former includes incorporating elements such as creativity, special effects, etc., in the design (Bhandari *et al.*, 2019). The latter includes guidelines related to clean, clear and symmetrical design, such as appropriately organising information (e.g., using symmetries, grouping elements and applying prototypicality), considering the volume of information (e.g., colour variability, visual clutter), and ensuring information discriminability (e.g. edge congestion, figure-ground contrast) (Miniukovich and De Angeli, 2015).

From another viewpoint, practitioners integrate cognitive psychology principles in visual design such as clarity in design, manipulation of size, utilisation of white spaces, selection of appropriate colours, avoidance of visual noise and connections between objects (Miniukovich and De Angeli, 2015). Conversely, a plethora of colours, information overload, and intricate shapes may hinder insights understanding (Pohl *et al.*, 2016). Gestalt principles of visual perception, rooted in psychology, including characteristics such as similarity, continuation, proximity, closure, symmetry, etc., are also used to create visually appealing and easily understandable visuals (Olshannikova *et al.*, 2015).

Some researchers claim that infovis and its aesthetics constitute a component of usability (e.g. Dix *et al.*, 2004), while others argue that it is a component of UX (e.g. Taylor *et al.*, 2011).

Alternatively, others suggest that they should be studied separately (e.g., De Angeli, Sutcliffe and Hartmann, 2006). Within the context of this study, we examine infovis and aesthetics separately.

2.2 Usability (UI), user experience (UX) and its evaluation methods
2.2.1 Usability (UI). UI seems to be the most critical factor in designing and building interactive products to ensure user satisfaction. Various researchers offer different definitions of UI. For instance, Nielsen (1994b) nests usability within systems acceptability including usefulness and compatibility. ISO 9241–11:2018 (2018) defines usability as the extent to which users accomplish their goals using the product with effectiveness, efficiency and satisfaction. Based on this definition, effectiveness, efficiency and satisfaction are considered as common usability measures. Usability is not a one-dimensional concept and contains various attributes (e.g., learnability, memorability, efficiency, errors and user satisfaction) (Mazumder and Das, 2014; Nielsen, 1994a). The importance of these attributes varies depending on the type of application and user requirements.

Due to the multifaceted nature of usability, various *Usability Evaluation Methods* (UEMs), or usability inspection methods, have been developed. UEMs are categorised as either "empirical" or "analytic" (Gray and Salzman, 1998), and they may utilise both qualitative and quantitative evaluation criteria. Usability testing is one of the most widely used empirical evaluation methods for detecting difficulties and errors encountered by users when using a service. This method typically involves examining variables such as errors, user satisfaction score, time spent on tasks etc (Hartson *et al.*, 2003). Analytic UEMs include techniques such as heuristic evaluation, walkthroughs which aim to stimulate a user's problem solving process and/or follow a scenario, and/or make inspections etc (Gray and Salzman, 1998; Nielsen, 1994c).

Heuristic evaluation has been widely used (e.g., Mazumder and Das, 2014), due to its ease of use and the fact that it is not time-consuming (Dix *et al.*, 2004). This method typically involves three to five evaluators who perform task-based evaluation based on platforms' compliance with usability principles (Nielsen, 1994c). The most well-known heuristic evaluation method is Nielsen's ten heuristic rules (Nielsen, 1994a) which include criteria such as (1) visibility of system status; (2) match between system and the real world; (3) user control and freedom; (4) consistency and standards; (5) help users recognise, diagnose and recover from errors; (6) error prevention; (7) recognition rather than recall; (8) flexibility and efficiency of use; (9) aesthetic and minimalist design; and (10) help and documentation.

2.2.2 User experience (UX). UI cannot guarantee the acceptance of a system, as the overall user experience makes a product stand out (Thüring and Mahlke, 2007). Designing user-friendly systems should focus on creating positive experiences rather than solely preventing usability problems. There is often confusion between usability and UX among researchers, and various UX definitions exist. According to ISO 9241–11:2018, UX is perceived as a consequence of a user's prior experiences, attitudes, skills, habits and personality, and it is defined as: "user's perceptions and responses that result from the use and/or anticipated use of a system, product or service". Taylor *et al.* (2011) define UX as a function of three variables, i.e. a user's internal state (e.g., expectations, mood and motivation), the characteristics of the designed system (e.g., complexity, usability and functionality), and the environment within which the interaction occurs. Overall, UX should care about how to fit user's goals, fulfil their needs, and prevent negative emotions.

One key difference between usability and UX lies in the inability of the latter to be assessed based on objective criteria (e.g. number of errors, time to complete a task) (Saket *et al.*, 2016). On the contrary, UX is more intricate, as it is associated with psychological and physiological concepts. It is measured by examining the emotions and feelings caused by using the system, and it is highly influenced by users' expectations and motivation (Law *et al.*, 2014).

There are many quantitative and qualitative *UX evaluation methods*. Research admits that hitherto the most common UX evaluation methods are mostly qualitative; these include lab tests and field studies (Law *et al.*, 2014). During lab tests, researchers collect experiential insights by observing users' expressions and emotions. Understanding users' emotions is essential in UX, and this can be also assisted by innovative techniques like design thinking (Chouki *et al.*, 2023). Conversely, in field studies, researchers observe and interview participants in real-life contexts to examine their expressions. In qualitative UX evaluation, researchers often employ exploratory user research techniques, such as ethnography. Additionally, they usually use audio or video recording (Dix *et al.*, 2004) to track users' expressions, and/or employ eye-tracking, prototyping tools and visual design to evaluate UX (Kashfi *et al.*, 2019). Similarly, surveys are sometimes utilised, as a means to receive feedback from end-users (Adagha *et al.*, 2017). In these cases, constructs such as flow, aesthetics beauty, enjoyment and attractiveness are measured (Law *et al.*, 2014).

A widely utilised method for assessing UX, UI and insights understanding is laboratory evaluation. This approach involves evaluating these elements "in a controlled environment where the evaluator monitors the use of a system, observes users" actions and reactions, and assesses users' feelings about the quality of the interaction (Lallemand and Koenig, 2017). Laboratory evaluation can involve a combination of methods such as usability testing, heuristic evaluations, task scenarios, observation, think-loud protocols to capture users' immediate experience, questionnaires to offer a consistent quantitative measurement, semi-structured interviews, etc (Alves *et al.*, 2014). These methods are applied in the examined case.
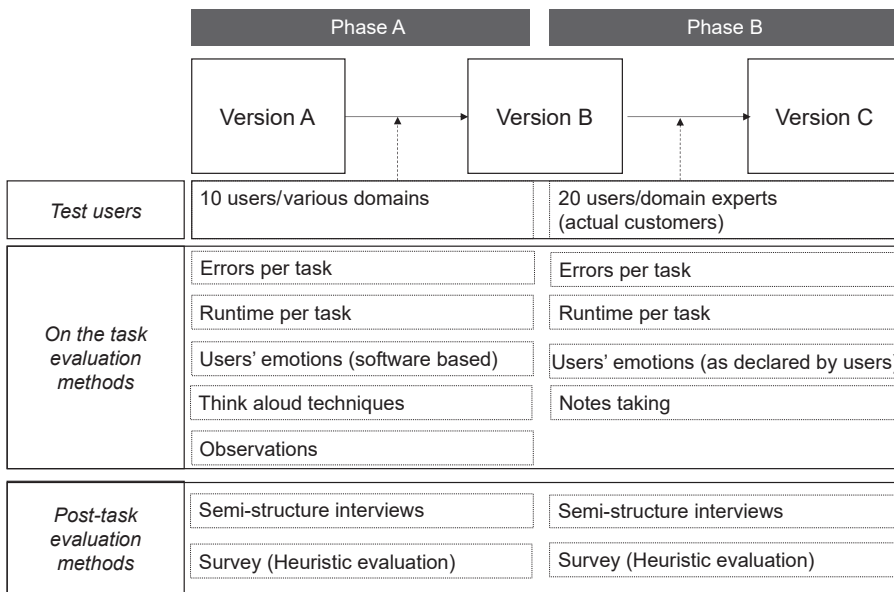
3. Empirical setting: a startup company offering a BA platform

This study adopts a case study approach to provide insights into the design and evaluation of BA platforms. Given the practice-based issue we face, where the experiences of the actors and the context of action are critical, feedback was gathered from the platform's actual end-users and the company's stakeholders (Benbasat *et al.*, 1987). This access to real-life contexts enriches the overall research process and underscores the importance of studying this empirical and contemporary phenomenon in depth (Yin, 2009). Adopting this method is valuable for understanding new phenomena that lack empirical substantiation (Eisenhardt and Graebner, 2007), as is the case with our startup, and for identifying how certain conditions change over time (Yin, 2009). Engaging with those "living the case" (Stake, 1995), the startup aimed to improve its BA platform through two redesign phases, guided by both unstructured and structured approaches. Feedback was gathered across three different versions from founders, test users and actual customers, supporting data triangulation. By involving individuals who represent the potential actual users, we aimed to simulate real-world usage scenarios and identify any areas for improvement. To triangulate and corroborate our insights, we used semi-structured interviews (15–30 min), observations and surveys, supported by software to capture users' emotions, and employed think-aloud techniques and note taking to better understand users while performing the task-based evaluation.

In more detail, Figure 1 presents the methods used in each redesign phase, distinguishing between on-task and post-task evaluations in a lab setting. The variation in on-task evaluation methods across different phases is due to coronavirus disease 2019 (COVID-19) restrictions (see section 3.3.3 for details). Additionally, Table 1 provides a detailed overview of the evaluation methods employed for each version of the platform.

3.1 Case study description

"ShopSights" (the name is fictitious to prevent anonymity) focuses on Big Data Analytics in the retail industry. The company has developed a "plug and play" [1] BA platform for analysing transactional and loyalty data within the grocery retail sector. The solution

	Phase A		Phase B	
	Version A	→	Version B	→	Version C
Test users	10 users/various domains		20 users/domain experts (actual customers)	
On the task evaluation methods	Errors per task		Errors per task	
	Runtime per task		Runtime per task	
	Users' emotions (software based)		Users' emotions (as declared by users)	
	Think aloud techniques		Notes taking	
	Observations			
Post-task evaluation methods	Semi-structure interviews		Semi-structure interviews	
	Survey (Heuristic evaluation)		Survey (Heuristic evaluation)	

Source(s): Figure created by authors

integrates with retailers' data marts, aiming to address predefined queries and visualise insights related to shopping behaviours to support demand and supply chain decisions. Its goal is to use advanced data analytics to provide retailers with valuable insights regarding their shopper behaviour in physical and digital stores from point-of-sales (POS) data. In more detail they have developed three modules:

(A) "Shopping segmentation": Identify shopping missions prompting customers to visit the store, such as purchasing products for breakfast, party, pastry making, sushi preparation etc. Identifying the shopping missions, the retailer can design bundle promotions (e.g., meal-deal-like offerings), adjust orders, determine secondary in-store placements, or even redesign the online or physical store layout to accommodate customer needs.

(B) "Customer segmentation": Segmenting shoppers by behaviour involves analysing purchasing history and creating segments based on shopping missions. This helped identify patterns in-store visits and highlight potential selling gaps. For example, if customers primarily visit for food but not for non-food items, this indicates a selling gap to address.

Apart from these advanced analytics results, for each shopping and customer segment, the end-users have access to descriptive statistics including peak days/hours, high-selling products, store Key Performance Indicators (KPIs), customer demographics, etc.

(C) "Product categories": Users can obtain information on specific product categories and brands related to shopping missions and preferred shopper segments. They can monitor which missions involve these products/brands and their associations with other products, and identify shopper segments and characteristics (e.g., demographics and preferences) for targeted marketing.

The BA platform uses retailer data, and with retailer agreements, ShopSights shares insights with other parties, like suppliers, about products and brands. ShopSights's clients are mainly grocery retailers or suppliers, and end-users typically have business and marketing backgrounds with limited BA knowledge. ShopSights developed a proof-of-concept (PoC) for its services, but the founders found the outdated design affected the visualisation, understanding and acceptance of the insights.

Phases		Phase A	Phase B
Users' profiles	Users	10 young entrepreneurs, members of an incubation centre	20 domain experts, executives of a grocery supplier (actual end-users of the platform)
	Mean Age	34	41
	Gender	6 males, 4 females	12 males, 8 females
	Role	3 business analysts 2 marketing managers 2 salespersons 1 project manager 1 software engineer 1 business development manager	4 advertising managers 3 marketing managers 3 business analysts 2 digital marketing managers 2 account managers 2 sales managers 1 business and strategy manager 1 merchandiser 1 e-commerce manager 1 consumer research manager
	Industry Expertise	Retail, e-commerce, gaming, advertising, banking, insurance	Grocery retail

Versions		Version A	Version B	Version C
Evaluation methods	UI	Heuristic evaluation survey based on Nielsen's principles	Heuristic evaluation survey based on Nielsen's principles	Heuristic evaluation survey based on Nielsen's principles
		Runtime per task (as measured by researchers)	Runtime per task (as measured by researchers)	Runtime per task (as measured by users)[a]	Runtime per task (as measured by users)[3]
		Number of errors (as measured by researchers)	Number of errors (as measured by researchers)	Perception about errors (as declared by users)[a]	Perception about errors (as declared by users)[3]
		Observations	Observations	Notes taking (from users)[a]	Notes taking (from users)[3]
		Semi-structured interviews	Semi-structured interviews	Semi-structured interviews	Semi-structured interviews
		Think-aloud techniques	Think-aloud techniques		
	UX	Users' emotions (software based)	Users' emotions (software based)	Users' emotions (as declared by users)[a]	Users' emotions (as declared by users)[a]
		Semi-structured interviews	Semi-structured interviews	Semi-structured interviews	Semi-structured interviews
		Think-aloud techniques	Think-aloud techniques	Notes taking (from users)[3]	Notes taking (from users)[3]
	Insights Understanding	Semi-structured interviews	Semi-structured interviews	Semi-structured interviews	Semi-structured interviews

Note(s): [a]In Phase B, due to COVID-19 restrictions, there were changes in data collection compared to Phase A
Source(s): Table created by authors

Like many start-ups struggling with time constraints, ShopSights is also facing similar challenges in swiftly improving and launching its platform. Their goal was to perform some quick modifications to the aesthetics and infovis elements to improve UI, UX and insights understanding. This happened in two phases until they finalised their platform. Throughout our interaction, we guided the startup on evaluating UI, UX and insights understanding.

3.2 Two iterations of redesigning the BA platform

The transition from the initial version of the user interface in the BA platform (Version A) to the final version (Version C) happened through a two-phase redesign process. Each phase likely involved design iterations, feedback gathering, and user testing to ensure that the final version (Version C) addressed the inefficiencies of the initial design. Below we present the changes made in each redesign phase, while in the next section, we present in detail the evaluation approach and methods used.

Phase A: Phase A involved the implementation of infovis. and aesthetic changes, guided by feedback from actual customers, the startup founders' own assessment, and the evaluation. During this design process, specific visual elements of ShopSights were altered while retaining the same information. In Version B, information was grouped into tabs to reduce visual noise; new visuals/charts were introduced to represent data; the colours, shapes, and layout of tables and diagrams were also changed. Figure 2 illustrates an example showcasing a comparison between the old and new interface screenshots.

Phase B: After receiving feedback from Version B during Phase A, this phase focused on refining again some infovis and aesthetic elements and leading to a new version of the BA platform (Version C). The changes made include various aspects such as converting text and tables into graphical representations, creating interactive data visualisations, altering charts, adding symbols, changing the colour palette, reducing unnecessary colours, creating symmetries, using more creative diagrams for data mining results and grouping visualised information differently. Figures 3 and 4 provide a comparison of a screenshot from Version B and Version C, both containing the same amount of information.

3.3 Evaluation approach

3.3.1 Test users' profiles. To evaluate the changes, we recruited 10 users who were young entrepreneurs and members of the incubation centre where ShopSights was incubated. The participants had diverse backgrounds and their expertise spanned across various domains (see Table 1 for details). During Phase B, we recruited 20 domain experts who served as executives for a grocery supplier (ShopSights client). These individuals were intended to be the actual end-users of the platform, utilising its content to aid decision-making. The recruited participants exhibited diverse backgrounds and held various roles, from marketing managers to business analysts. Table 1 summarises the test users' profiles that evaluated the BA platform.
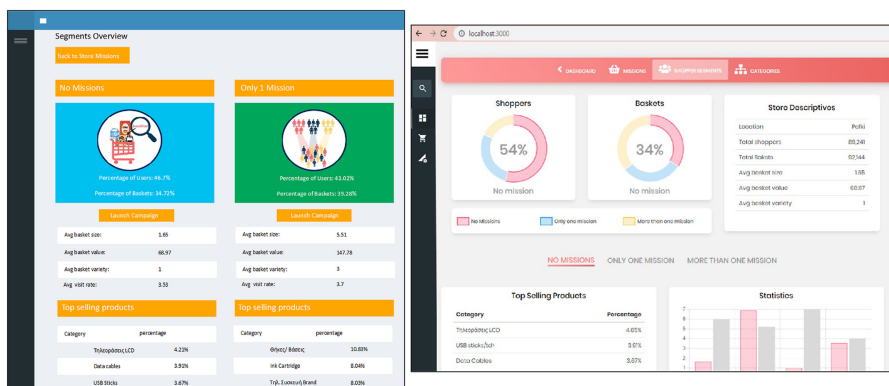

Source(s): Figure courtesy of ShopSights

Figure 2.
A screenshot of
Version A (left) and
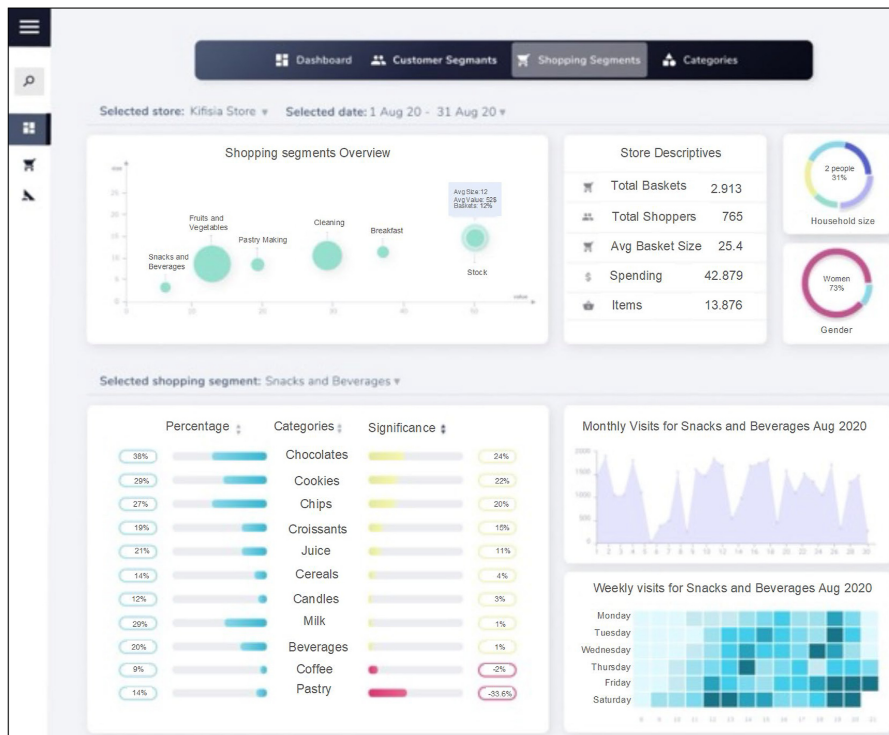Version B (right) –
Module B view

Figure 3.
A screenshot of
Version B – Module
A view

Source(s): Figure courtesy of ShopSights

3.3.2 Interaction with the BA platform. During both phases, the test users were asked to perform specific tasks. Moreover, to support a realistic evaluation, we invited participants to browse the system for some time prior to starting the task execution. The tasks include the following:

(A) Finding the shopping mission that has the highest average basket value in-store "X".

(B) Finding the top-selling product in this shopping mission and the most high-selling day.

(C) Finding the top-selling product of brand "Y" in-store "Z".

(D) Finding the customer segment that includes the most shoppers.

Source(s): Figure courtesy of ShopSights

Also, after the task execution users kept browsing the platform to share any additional thoughts and to reply to some specific questions to assess whether they understood or not the insights as explained below.

3.3.3 Evaluation methods. During users' interaction with the several versions of the platform, we conducted the actual evaluation and collected the data. For this purpose, a combination of quantitative and qualitative techniques was used. See below (and in Table 1) the methods used in detail to evaluate UI, UX and insights understanding in all three versions of the platform.

UI: Participants assessed usability elements through a combination of quantitative and qualitative methods conducted in a laboratory setting. Quantitatively, users completed a heuristic evaluation survey (as detailed in Table A1 in the Appendix) to gauge the system's usability. This survey utilised Likert scale questions (ranging from 1 for "totally disagree" to 5 for "absolutely agree") aligned with Nielsen's principles (see 2.1.1). Users also rated the importance of each factor for the BA platform using the Likert scale. Task run times and the frequency of errors were recorded for each participant. Qualitatively, we employed observation techniques and debriefing semi-structured interviews after the interaction with the platform to understand users' sources of confusion and their overall experience. While on-task evaluation also included thinking-aloud techniques.

UX: Participants assessed the perceived UX by observing and recording users' expressions and comments during task execution. Additionally, specialised software was utilised to identify emotions through more pronounced facial expressions, such as anger,

sadness, neutrality, surprise and happiness. The on-task evaluation also included thinking-aloud techniques. To gain further insights into UX, participants were prompted during semi-structured interviews at the conclusion of the evaluation. They were asked to describe their experience with the platform using a single word and provide justification for their choice. This additional step aimed to extract further insights into users' subjective experiences and perceptions of the platform's usability and overall effectiveness.

Insights understanding: After completing the tasks, as part of the semi-structured interviews, participants were questioned about their comprehension of the analysis results. Some sample questions aimed at assessing insight understanding included explaining the content of certain screens, interpreting specific visualisations, explaining how these insights contribute to decision-making, etc.

In summary, it's important to highlight that during Phase B, adjustments were made to the evaluation methods due to COVID-19 restrictions. Firstly, users' task runtimes were measured by users, the same happened for the number of errors. Secondly, the observational component, which included thinking out loud, was replaced with the instruction for users to take notes on their observations. Furthermore, emotions were not monitored by software; instead, users were asked to note how they were feeling and elaborate on it during the interviews.

4. Evidence from the case study
In this section, we present the impact of the alterations related to aesthetics and visualisation, on usability, UX and insights understanding during Phases A and B.

4.1 UI evaluation
In the usability evaluation, we employed a heuristic evaluation survey, recorded task execution metrics (run time and number of errors) and complemented these with brief interviews. Table 2 provides a summary of the heuristic evaluation survey results for Phases A and B, helping identify the more usable platform version.

The variable "r" represents the average compliance degree of the platform with each rule, while variable "w" represents the average significance level. For example, during Phase A, participants who evaluated Version B, answered that they "absolutely agree" ($r = 5$) with

| Nielsen rule | Phase A | | | | | | Phase B | | | | | |
	rA [1.5]	wA [1.5]	eA	rB [1.5]	wB [1.5]	eB	rB [1.5]	wB [1.5]	eB	rC [1.5]	wC [1.5]	eC
1	3.00	4.81	14.43	4.33	4.86	21.04	3.39	4.93	16.73	4.38	4.90	21.46
2	2.87	4.63	13.29	4.17	4.66	19.43	3.81	4.42	16.86	4.56	4.79	21.84
3	3.17	4.91	15.56	4.22	4.89	20.64	3.28	4.96	16.27	4.01	5.00	20.05
4	3.25	5.00	16.25	5.00	5.00	25.00	4.00	4.96	19.84	4.92	5.00	24.60
5	2.75	4.86	13.37	4.50	4.82	21.69	3.19	4.81	15.36	4.54	4.93	22.38
6	1.50	4.66	6.99	2.67	4.64	12.39	3.85	4.79	18.44	3.88	4.89	18.97
7	1.75	4.10	7.18	4.33	4.00	17.32	3.69	4.45	16.42	4.43	4.12	18.25
8	2.25	4.66	10.49	4.33	4.64	20.09	3.54	4.78	16.92	4.21	4.73	19.91
9	3.25	5.00	16.25	5.00	5.00	25.00	4.00	4.96	19.84	4.92	5.00	24.60
10	2.75	4.60	12.65	4.00	4.70	18.80	3.38	4.55	15.40	4.69	4.64	21.76
	ΣeA		126.45	ΣeB		201.40	ΣeB		172.08	ΣeC		213.84

Table 2.
Heuristic evaluation, results from Phase A (Version A vs Version B); and Phase B (Version B vs Version C)

Source(s): Table created by authors

Nielsen rule 4 and at the same time they declared that this aspect is "really significant" ($w = 5$). The degree of compliance "e" for each rule is calculated by multiplying "r" and "w". Similarly, the overall degree of compliance, i.e. the overall usability score of the system is calculated by using $\Sigma(ei)$ (i depicts each rule). Hence, for example, "ΣeB" (Version B) equals 201.40, whereas "ΣeA" (Version A) equals 126.45. Since the average degree of compliance of Version A is higher than the old one (Version B), it seems that the new design corresponds better to Nielsen's rules, and therefore, it is more usable.

In Phase B, expert users assessed both Version B and the newly designed Version C. A comparison between Phases A and B of Table 3 reveals that non-domain expert users evaluating Version B in Phase A provided higher scores than domain experts who assessed the same Version B in Phase B. This discrepancy may be attributed to the fact that our Phase A test users were young entrepreneurs who might be more familiar with BA platforms. However, when comparing the usability scores between Version B and Version C, it is evident that the latter received a higher rating in usability from domain experts compared to Version B. This suggests that the changes in aesthetics and visualisation positively impacted the overall usability of the platform.

Table 3 summarises the results for task run times in both Phases. Each time the new version exhibited shorter execution times. For instance, the total average run time in Phase A for Version A was nearly 2.5 times longer than in Version B. Additionally, users evaluating Version A provided an average of 2.2 incorrect answers before reaching the correct one, while users assessing Version B averaged only 0.8 wrong answers. Qualitative insights were gathered through semi-structured interviews. Users evaluating Version A attributed the confusion to information overload on each screen. In contrast, during Phase A, users assessing Version B did not identify significant factors causing confusion.

| | Average run time in minutes | | | |
| Task | Phase A | | Phase B | |
	Platform A	Platform B	Platform B	Platform C
A	2.56	1.08	1.12	0.46
B	1.28	0.45	0.53	0.34
C	1.05	0.50	0.56	0.38
D	3.45	1.26	1.33	0.58
Total	8.34	3.29	3.54	1.61

Source(s): Table created by authors

In Phase B, due to COVID-19 restrictions, we conducted an asynchronous evaluation since we couldn't visit the supplier. This approach presented challenges, particularly in tracking errors and execution times. Users were requested to monitor these aspects on their own and provide comments on-task execution time and errors. According to users' feedback, navigating and completing tasks in Version B posed difficulties, leading to multiple errors before finding the correct answer. Also, two of them mentioned that they thought they had found the correct answer for task D; however, after looking at the given notes, they realised that their answers were wrong. Two others mentioned that they quit task D. When they were asked about the reasons for the confusion, they mentioned that they found Version B boring and not attractive enough to spend more time on. One of them mentioned: "*I was confused as the platform design was boring, it had many tables, and it didn't attract me to find the answers quickly*". Some users reported encountering challenges stemming from information overload, while others highlighted spending considerable time navigating through various screens to locate the correct answer. A comparison between users in Phases A and B, both assessing

Version B, suggests that the latter group may be more demanding, possibly due to their limited interaction with BA platforms. Despite Phase A users being young entrepreneurs rather than domain experts, they found certain aspects of the BA platform more accessible.

Most users who evaluated Version C during Phase B mentioned that they do not think that they encountered many errors. This is highly subjective, though this is still an indication. One of them mentioned that they had issues regarding task D and they spent more time on this. Also, the majority of users mentioned that they completed the tasks relatively easily without spending much time. One mentioned that *"the time that I spent on the tasks is quite similar to the time that I would spend when navigating in our CRM platform to complete my daily tasks"*. Another mentioned that they found the information desired relatively easy and they were *"satisfied because I can see all the available info gathered in one screen"*. Regarding Version C, users could not spot something specific that caused their confusion. Some of them mentioned something abstract such as *"my background"* or *"my age"*. The above are some indications that the changes we performed in BA's platform aesthetics and data visualisation somehow affected positively the usability of Version C.

4.2 UX evaluation
During Phase A, the users who evaluated Version A spent much time in navigation and seemed frustrated and stressed based on their expressions. Similarly, based on their comments, they found it difficult to understand which page contained the requested information. Some users spent a lot of time scrolling on the same page without being able to find the answer they were asked. They also reported that the bright colours distracted their attention. It is remarkable that one user while executing the task-based evaluation of Version A, thinking out loud, they mentioned *"this visual is crazy"*, and another one said, *"so much noise to find a simple answer"*. When they were asked to describe the BA platform in a few words, the most popular answers were *"chaotic", "complicated" and "unpredictable"*. Users who evaluated Version B, although they spent less time completing the tasks, they encountered some issues, as well. For example, several users were trying to interact with the visuals, although these visuals weren't interactive. Others tried to sort the information from the tables, but they did not have this capability. During the evaluation, they did not show any strong negative emotions, or strong positive emotions, as well. When they were asked to describe the platform, they used words such as *"pleasurable", "enjoyable" and "presentable"*.

During Phase B, the domain users who evaluated Version B reported that they were anxious to complete the given tasks. Also, although they did not report any strong feelings during the execution of tasks A–C, they noted that they were frustrated and nervous for spending a lot of time searching and scrolling how to complete task D. Indicatively, a user mentioned *"this (meaning task D) seems like a riddle"*. Some of them described the platform as *"ok", "a platform like all the rest", "decent", "a nice one", "indifferent", "mad", "confused", "nice but confusing", "many numbers difficult to spot patterns" and "busy"*. Users who evaluated Version C didn't express any strong emotions, in their notes they reported that they were *"calm", "confident"* about their answers and *"relief"*. Moreover, users who evaluated Version C described it as *"insightful", "actionable", "visually beautiful", "seems you can find fast what you look for", "I can easily understand the information", "eye-catching", "clear", "well-put" and "modern"*. Examining all the above facts based on users' comments and emotions, we may say that the Version C of the BA platform and the alterations in the aesthetics and infovis improved the overall UX of the platform.

4.3 Insights understanding evaluation
During Phase A, the users who evaluated Version A claimed that it was difficult to understand the insights and the business value of the BA results. During an interview,

a business analyst mentioned: "*If I was the decision maker of this company and I had to make a decision based on this (version A), they would probably fire me*". Moreover, almost all the users reported that due to the information overload on each screen, they were having difficulty understanding the insights. They also mentioned that understanding the insights is difficult due to the existence of multiple tables and the lack of visuals': *"The lack of visuals made it difficult to spot the differences in the data and understand the insights displayed"*. One of their main problems was the absence of symbols to immediately understand what information was displayed in each visual. The users were evaluating Version A and they were asked to describe the information displayed, they spent more time describing the information they were viewing, and they were making many assumptions. Some of them also were waiting for a confirmation of their answers, which indicates uncertainty. Conversely, users assessing Version B offered more confident answers and provided more accurate descriptions of the analysis results. Nevertheless, their lack of expertise prevented them from fully comprehending all insights, as well as translating them into actionable decisions. They appeared to understand some of the content presented and made assumptions about the remainder.

The domain experts who evaluated Version B (in Phase B) were able to understand almost most of the content and the insights displayed. In their majority, they gave accurate descriptions. However, not all of them were able to deeply comprehend the insights. Some users appeared somewhat nervous, expressing frustration with the platform's perceived difficulty in comprehending insights. One user remarked, *"It is not my job to think that much when we invest in a platform. I am not going to guess; I want the platform to tell me what is displayed here"*. Another user stated, *"I am not a business analyst, and it is not my job to solve riddles. This platform is supposed to help me understand the insights without trying that much"*. In a similar vein, another user commented, "*Too much info but nicely viewed. I need to find a way of using it to exploit the insights"*, while another agreed, stating, "*It contains useful info, but it does not help me find the insights"*. Notably, some users evaluating Version B acknowledged the absence of certain visuals but, being familiar with tools like Excel, expressed satisfaction with the presented tables and their ability to understand the insights.

On the other hand, the users who evaluated Version C gave correct answers about almost all the screens they were asked to explain. They seemed to understand almost every aspect of the platform and some of them were happy, energetic and proud when they were describing the information displayed and the respective insights. Some of them not only fully comprehended the insights displayed, but they were linked these insights with actions and decisions they could support. The business and strategy manager of the grocery supplier mentioned "*I am certain that the knowledge and insights derive from this platform as-is are attainable by most of the marketing staff"*. Others mentioned that "*the insights are intelligently visualised by the platform, and I don't need to put a lot of effort"*, and that "*these visuals add value to my work and my daily tasks"*. Of course, as expected, not everything was that clear for every user. For example, there were two people who mentioned that they need to put a lot of effort into understanding the insights, and it needs more modifications to be able to connect the insights with actions. Also, another mentioned that they understand the insights, but they need to "*deep dive in the charts and spend time to find the value"*. Overall, the visual alterations to the BA platform appear to assist users in better-comprehending insights and, at times, translating them into actions.

5. Discussion
We are in the era of big data, and as such, BA platforms are important to assist companies in supporting demand and supply chain operations (Raza *et al.*, 2023). However, if a BA platform is not user-friendly and does not provide actionable insights, it may fail to effectively support

these operations, resulting in lower-quality decision-making (Li *et al.*, 2022). Existing literature primarily focuses on different aspects of the design of analytics platforms, including UI, UX and visualisation aspects (González-Torres *et al.*, 2013; Gutiérrez *et al.*, 2020; Pohl *et al.*, 2012).

Recognising the importance of UX/UI in platforms, existing literature includes several studies that focus on models, principles, and rules for evaluating usability and UX (e.g., Mazumder and Das, 2014), or on the application of these principles (e.g., Lavie and Tractinsky, 2004; Mazumder and Das, 2014). However, there is only a limited subset of literature specifically addressing the evaluation of these elements in BA platforms (e.g., Pohl *et al.*, 2012).

Apart from the lack of UX/UI research in BA platforms, another gap is related to the visualisation and understanding of insights. Regarding visualisation, some studies examine visualisation elements (i.e. aesthetics and information visualisation) and study how to evaluate them (e.g., Banissi *et al.*, 2014) or focus on the factors influencing visualisation and provide guidelines (e.g, Franconeri *et al.*, 2021; Luo, 2019). There are also some studies that highlight the importance of insights understanding by the end-users (e.g., Vázquez-Ingelmo *et al.*, 2024); though, they do not provide some evidence for example on the impact of this on BA platforms etc. On the other side, academia underscores the need to explore the interplay between visualisation, aesthetics and insights understanding (Chen, 2005; Vázquez-Ingelmo *et al.*, 2024), particularly in the context of BA platforms, given their role in visualising diverse data. Despite this recognition, there is a notable scarcity of research addressing this relationship, highlighting a critical gap in the literature.

To address the above gaps and examine the impact of visualisation on UI and UX in BA platforms while emphasising the importance of insights understanding, this research provides empirical evidence by following the iterative process of a startup as it develops a retail BA platform. Specifically, the startup underwent two rounds of changes. As a result, we collaborated with the startup to conduct evaluations across three versions of the same BA platform. We used a combination of well-known evaluation methods such as heuristic evaluation surveys, computation of errors and runtimes, observations, think-aloud techniques, interviews and emotions recording.

5.1 Practical implications/learnings

Small ventures lack time and resources to meticulously evaluate and change their BA platforms. To find guidelines on what to test and how they must search multiple sources and delay the launching of their product. This paper offers them practical knowledge on what they should test and how while designing their BA platforms. The background section overviews the evaluation methods they can use to assess the UX/UI and insights understanding of their BA platforms. The case described and Table 1, provides some more tangible recommendations on what to test and how. While the findings offer some valuable insights for businesses undertaking similar redesign endeavours.

In more detail, our findings demonstrated that each phase of the redesigned platform interface performed better compared to its predecessor. Thus, alterations made to the aesthetics and information visualisation of this BA platform seem to positively impact the overall UI and UX of the platform, which is in line with what the literature suggests (Kashfi *et al.*, 2019; Vázquez-Ingelmo *et al.*, 2024). Additionally, our findings underscore the impact of these modifications on the insights' understanding among platform users, an important element in practice, yet it is underexplored in research (Vázquez-Ingelmo *et al.*, 2024). The per-phase evaluation process significantly improved our understanding of the impact of each change, making it a highly recommended practice. By evaluating changes in phases, we can identify potential issues early and make necessary adjustments before they escalate.

In our case, we identified that young entrepreneurs who were more familiar with BA platforms found it easier to use the BA platform. As such, it is advisable to assess the impact of modifications by engaging with test users and individuals from diverse backgrounds with different levels of familiarisation with BA platforms, as also suggested by others (e.g., Miniukovich and De Angeli, 2015; Vázquez-Ingelmo *et al.*, 2024). This step should be taken before reaching out to customers, especially if direct evaluation is challenging.

Providing the small venture practitioners with some more tangible insights based on our case we can say the following:

First, we observed that each newly designed platform version was rated higher in terms of usability using Nielsen's rules. Also, it seems that Nielsen rules such as "consistency and standards" (rule 4), "recognition rather that recall" (rule 7) and "user control and freedom" (rule 3) are important to consider when designing BA platforms. So, one quick key takeaway for practitioners is to pay attention to the colour uniformity of buttons, diagrams, and images. This aligns with the literature suggesting that a plethora of colours, information overload, and intricate shapes may hinder the usability of the platform (Pohl *et al.*, 2016). In our case, these created better experiences for users and their emotions seemed to be more positive. Overall, monitoring emotions can help evaluate the BA platform efficiently, a practice commonly suggested by psychologists and researchers (e.g., Thüring and Mahlke, 2007).

Second, practitioners should be aware that end-users struggle when they have to remember their previous actions while performing tasks. As such, they should prioritise providing clear navigation paths and minimising the need for users to recall past interactions. This finding is supported by existing literature; for instance, Nielsen (1994a) advocates for systems that do not force users to remember information from one section or screen to another, corresponding to the need for clear navigation paths and minimising memory load. Based on our findings, navigation and the ability to interact with the platform are important factors that practitioners should examine when designing BA platforms. Existing literature (Heer and Shneiderman, 2012; Luo, 2019) supports this, demonstrating that interactive dynamics in visual analysis significantly enhance user engagement and usability. Moreover, users should be able to easily find and access the features and information they need within the platform. On top of this, we also suggest that interactive elements such as clickable charts, hovering over charts, and drag-and-drop functionalities make the platform more engaging and user-friendly. For instance, users might appreciate the ability to interact directly with data visualisations to drill down into specific insights or adjust parameters dynamically. Furthermore, users should be able to easily find and access the features and information they need within the platform. For example, implementing a clear and logical menu structure, providing breadcrumbs for easy navigation back to previous pages and incorporating intuitive search functionality can all contribute to a smoother user experience.

In the same vein, incorporating features that offer users control and freedom within the platform can significantly enhance their experience. Users value being able to undo an action in case of an error, to be able to easily navigate to the home screen from anywhere and to be able to find the pages they were searching for quickly and easily. Such elements can also improve the time spent for each task. To assess it in our case we monitored the runtime per task, as such we recommend companies to measure the same as a crucial element in the redesign of a BA platform. Several studies highlight the significance of freedom and customisation in various contexts, such as health or educational platforms. For instance, Aljohani *et al.* (2019) demonstrate that personalised layouts, such as data filtering, draggable widgets and resizable elements, play a crucial role in enhancing UX by aligning with individual preferences. This principle is also highly relevant to BA platforms, which may have users with diverse backgrounds and varying levels of familiarity with analytics tools (Vázquez-Ingelmo *et al.*, 2024). By allowing users to personalise their dashboards, choose their preferred data visualisation methods, and adjust tool settings, these platforms accommodate

a wide range of expertise levels and learning styles. In this regard, providing users the freedom to personalise their dashboard layout is essential. Instead of a fixed arrangement of charts and graphs, BA platforms could allow users to drag-and-drop widgets, resize or hide elements according to their specific workflow needs and priorities. Additionally, offering customisable filtering and sorting options for data can further enhance UX. Although Version C of the platform did not fully integrate these features, they emerged as significant in short interviews, underscoring the importance of such customisation for optimising user engagement and task efficiency.

According to our findings, it is reported that visual interventions and improvements, aided users in better understanding the analysis results. They easily comprehended the insights, and sometimes they were connecting the visualised insights with actions and decisions. Several participants reported that "*these visuals add value to my work and daily tasks*" aligning with the concept of "perceived usefulness" found in existing literature (Adagha *et al.*, 2017). While we did not specifically measure perceived usefulness, it is crucial to consider when evaluating insight comprehension in BA platforms. Our research suggests that to enhance perceived usefulness, it is essential to avoid bright and vibrant colours and maintain visual consistency throughout the platform. This includes using consistent colour schemes, fonts, and iconography across different visualisations and interface elements. For example, having a standardised colour palette that avoids overwhelming or distracting colours can help maintain visual harmony and focus users' attention on the most important information. In our case, the pal colour in Version C was reported to offer more positive emotions to users. Closing, the inclusion of symbols on the charts and the creation of symmetries (see bottom left of Figure 4) are also important elements to consider. Gestalt principles of visual perception support this view, and other researchers agree that symmetry can produce visuals that are both aesthetically pleasing and easy to comprehend (Olshannikova *et al.*, 2015).

Moreover, the conversion of text and tables into visuals, the separation of primary and secondary information, and the grouping of the visualised information are important factors that practitioners should scrutinise when they design a BA platform. For example, in Version 2 (see Figure 3) the tabular representation of the days and the hours seemed boring to the users. While the heatmap in Version 3 (see Figure 4) was perceived better as users reported that they could easily spot patterns. Utilising heat maps with a consistent gradient is recommended by other researchers (Lobanova *et al.*, 2024). They also suggested that assigned colours for trends can be applied across different visualisations, enabling users to quickly identify whether a trend is rapidly growing or well-established without needing to reference the matrix.

Contemporary graphics such as the packed bubble chart (see Figure 3) often pose challenges for certain user groups, particularly older individuals, who may find these visualisations less intuitive. In contrast, a simpler representation, such as a traditional bubble plot (see Figure 4), appears more accessible and straightforward to them. Feedback from test users highlighted a prevalent issue in design practices: the assumption that more elaborate or "fancier" visuals inherently lead to better UX. This assumption often leads companies to prioritise visually complex graphics under the belief that they enhance the appeal and effectiveness of data presentations. However, this belief can be counterproductive. Elaborate visualisations can sometimes hinder rather than help comprehension, particularly for users who may not be as familiar with or adept at interpreting complex visual formats. This aligns with existing research which suggests that overly complex graphics can create cognitive overload and confusion, especially for users who are not well-versed in data interpretation (Hollender *et al.*, 2010).

On the other hand, the perspective held by the founders of ShopSights, that more "innovative or fancy visuals are beneficial for pitching and investor presentations", reflects a different aspect of visual design. According to their viewpoint, sophisticated visuals can enhance the perceived value and attractiveness of their product during high-stakes presentations, even if they are not necessarily optimal for everyday user interaction. This

dichotomy is partially supported by existing literature. For instance, Chouki *et al.* (2023) argue that innovative visualisations can indeed offer an enhanced UX by providing novel ways to engage with and interpret data. While more complex visuals might not always be practical for everyday use, they can still play a crucial role in specific contexts, such as marketing and investment scenarios, where demonstrating the potential of a product or idea in an impressive way is essential.

Overall, an important challenge that emerged from this example lies in balancing visual complexity with usability. Effective design should consider the context of use, the expertise level of the audience and the specific goals of the visualisation. Striking the right balance can ensure that visualisations are not only appealing but also functional and accessible to all users.

To help companies improve their performance using insights from the paper, Table 4 offers a structured overview of key areas to focus on and specific actions to take for benchmarking, evaluating and enhancing BA platforms. This table provides details on methods to assess BA platforms and outlines practical practices to follow. It serves as a practical guide for organisations to identify strengths and areas for improvement.

Area	Action
Methods to assess UX/UI and insights understanding	The following methods are recommended to assess each element • *UI evaluation:* errors, user satisfaction score, time spent on tasks, heuristic evaluation, walkthroughs (with notes taking), scenario following, inspections. (Semi-) structure interviews and observations can be also helpful • *UX evaluation:* ethnographies, surveys, lab tests and field studies to monitor users' expressions and emotions. This can be facilitated via eye-tracking, prototyping tools and software. (Semi-) structure interviews can be also used • *Insights understanding:* (Semi-) structure interviews based on scenarios/tasks
Benchmark against previous versions and users/	Compare each redesigned phase with its predecessor to measure improvements in UI, UX and insights understanding. Try to split the redesign phases into measurable steps Find test users with diverse backgrounds
Nielsen's usability rules	Focus on rules like "consistency and standards", "recognition rather than recall", and "user control and freedom" to enhance platform design. Pay attention to the colour uniformity of buttons, diagrams, and images
Navigation and interactivity	Simplify navigation, ensure clear navigation paths, reduce the need for users to recall past actions, and incorporate features like clickable charts, hover effects and drag-and-drop functionalities
User control and personalisation	Provide user control and customisation options. Allow them to undo actions, navigate easily and personalise their dashboard layout with drag-and-drop widgets and customisable filters
Visual consistency	Maintain a consistent visual design. Use a standardised colour scheme, consistent fonts, and iconography to avoid overwhelming users and to highlight important information
Effective visualisation	Convert text and tables into easy-to-understand visuals. Use simple and clear visualisations like heatmaps instead of complex graphics, and ensure the visual design is straightforward
Intuitive design for non-expert users	Ensure visualisations are intuitive by balancing visual appeal with ease of use. This approach will help avoid cognitive overload and enhance accessibility for all users, particularly those who are less familiar with BA platforms and who may be less tech-savvy

Source(s): Table created by authors

Table 4.
Overview of recommendations for BA platform assessment and design

5.2 Limitations and future research

In this study, our primary aim was not to claim any methodological contribution or rigorously assess the visual changes made by the startup. Instead, we focused on tracing the startup's visual redesign journey and aiding them in a quick and pragmatic evaluation, given their time constraints for a speedy platform launch. While acknowledging the potential for errors or limitations in our evaluation, our goal was to emphasise the significance of infovis and aesthetics in UI, UX and insights understanding. Future research could further delve into suggesting more rigorous visual changes and measuring their impact on UX/UI and insights.

Building on the above, in this research, we do not support that only visual changes are adequate to ensure the acceptance of a BA platform, but we pinpoint the importance of visualisation in BA platforms. In addition, our goal is not to evaluate the visual changes made and we do not admit that we created a visual optimal BA platform. That is the reason why we do not present common aesthetic evaluation and information visualisation methods. However, future research may focus on deriving visual design principles while designing BA platforms, and present methods for their evaluation.

Domain knowledge is considered as one of the most critical factors in the understanding of insights and the analysis results (Vázquez-Ingelmo *et al.*, 2024). However, in our study, it seemed that users who evaluated Version B during Phase A, although they weren't domain experts, their prior experience as startuppers in building BA platforms, resulted in rating the platform better than the domain experts who evaluated the same Version B during the Phase B. We do not admit that we can generalise this finding; however, examining whether prior experience in similar BA platforms is more important than domain knowledge in the acceptance of a BA platform and a system in general, is a great avenue for future research.

Another important aspect is that in the current study, the users interacted with the BA platform for a short period of time before evaluating it. However, examining the post-acceptance and post-adoption of such BA solutions is a fruitful area of research (Batziakoudi *et al.*, 2020).

An additional limitation of this research is that due to COVID-19 restrictions, we were unable to visit the grocery supplier and observe users during the task-based evaluation. As a result, we had to extract their emotions based on their claims rather than using software, as was done in Phase A of this study. Additionally, some usability metrics (e.g., runtime and errors) were measured subjectively. Future research may address these limitations.

6. Conclusions

Our goal in this paper is three-fold. Firstly, we aim to underscore the pivotal role of aesthetics and information visualisation within BA platforms. Secondly, we advocate for a holistic approach to evaluating BA platforms, emphasising that we should not only examine one element such as UI or UX; but we should also pay attention to the insights understanding. By considering insights and understanding alongside traditional usability metrics, businesses can obtain a more nuanced understanding of their platform's effectiveness and user acceptance. Lastly, we provide insights and some learning on what small companies should focus on when developing BA platforms. It is well-known that start-ups often lack the luxury of time for extensive reactions and frequently select quick and dirty solutions to innovate, survive, and go to market as fast as they can (Corvello *et al.*, 2024; Karpinskaia, 2023; Zamani *et al.*, 2022). Our selected case study illustrates a startup facing time constraints while rapidly evolving its BA platform to meet market demands.

Notes

1. A non-customisable BA platform with predefined screens. Analytics, including model retraining and chart updates, occurs automatically with new datasets. Weekly in our case.

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Appendix

Question	Nielsen rule
1. Words, descriptions and symbols were fully understood	2
2. I could always go back or undo an action in case of an error	3
3. The design was consistent. Buttons, diagrams and images have schematic and colour uniformity	4, 9
4. I was not confused or made any mistake while performing the tasks	6
5. I did not have to remember my previous actions while performing the tasks	7
6. Being an unexperienced user, I found it easy to follow the steps I had to perform	8
7. I could easily understand what the charts show	2, 8
8. I could easily navigate to the home screen from anywhere	3
9. I could correct any action taken by mistake quickly and easily	5, 1
10. I could find every page I was requested quickly and easily	3, 1
11. I was able to find more information about each platform element easily	10
Source(s): Table created by authors	

Table A1.
Heuristic evaluation survey

About the authors
Dr Anastasia Griva is an Assistant Professor in Business Information Systems at the University of Galway, Ireland. She has worked on research commercialisation by establishing two AI and analytics start-ups which have raised more than 1.3 M from VC funds. Her research interests lie in the areas of Business Analytics, Responsible AI and innovation. She has published in edited books, academic journals (e.g., Information Systems Journal, Information Systems Frontiers, IT and People, International Journal of Information Management, Journal of Retailing and Consumer Services, Expert Systems with Applications, IEEE Software, Journal of Decision Systems), and proceedings of international conferences (e.g., ECIS, MCIS, EGOS). Anastasia Griva is the corresponding author and can be contacted at: anastasia.griva@universityofgalway.ie

Dr Angeliki Karagiannaki is a part-time Lecturer at the Departments of Management Science and Technology, and Informatics of the Athens University of Economics and Business (AUEB). She is also a founding member and the managing director of ACEin, the incubation centre of AUEB. She holds a PhD from AUEB and a Masters' in Management Science and Operational Research from Warwick Business School. Her research interests lie in innovation and entrepreneurship, research commercialisation, and supply chain management innovation. Angeliki has had active participation in several national and European research projects and has published articles in many academic Journals and conferences.