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Applying the Technology Acceptance Model to Risk Communication Dashboards: A case study

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Abstract

Purpose: This study examines how the design characteristics of risk communication dashboards influence user acceptance in Small and Medium-sized Enterprises (SMEs). As dashboards become essential for data-driven decision-making, identifying which visual and functional elements drive adoption is critical. The research focuses on features that most strongly affect perceived usefulness (PU) and perceived ease of use (PEOU), two core constructs of the Technology Acceptance Model (TAM), within organisational risk communication and decision support.

Methodology: Based on the extended TAM3 framework, three design characteristics: Notifications and Alerts, Data Context, and Education level were analysed, with Age and Data-to-Ink ratio as moderators. Data were collected from 67 SME executives through an online survey. Structural relationships were tested using Partial Least Squares Structural Equation Modelling (PLS-SEM) to assess reliability, validity, and model fit, leading to the evaluation of nine hypotheses.

Findings: The results indicate that Notifications and Alerts significantly enhance PU, while Data Context improves PEOU. PU positively influences Attitude Toward Use (ATU), which emerges as the strongest predictor of Behavioural Intention (BI). Education level negatively affects PU, Age moderates the relationship between dashboard functionality and PU, and Data-to-ink ratio moderates the effect of Data Context on PEOU.

Practical implications: The findings offer actionable guidelines for designing dashboards that improve clarity, usability, and risk communication efficiency in SMEs, thereby fostering greater engagement with digital decision-support tools.

Originality: This study extends TAM3 to the domain of static risk communication dashboards, demonstrating that design elements are critical determinants of user acceptance in Industry 4.0 decision environments**.**

Keywords: Decision support systems, Decision analysis, Information systems, Risk Communication Dashboard; Dashboard design

1 Introduction

In the context of the fourth industrial revolution, small and medium-sized enterprises (SMEs) face intense competition to secure market share, satisfy customer needs, and sustain profitability. Although SMEs benefit from inherent organisational agility, their managers often struggle to formulate coherent and optimised strategic plans, due to constraints related to time, methodology and expertise (Gueguen et al., 2016). To address these challenges, it is imperative to equip managers with methodologies that enhance employee involvement in decision-making processes, thereby enhancing engagement and imbuing work with purpose (Wang et al., 2022; Benoliel & Somech, 2014; Saks, 2022).

Dashboards have emerged as valuable business intelligence tools, offering a comprehensive overview of company performance and demonstrating positive correlations with employee productivity (Velcu-Laitinen & Yigitbasioglu, 2012). Effective dashboards require both functional capabilities and visual design properties (Few, 2006; Almasi et al., 2023). Functional characteristics define the capabilities and interactivity of a dashboard, while visual characteristics ensure that data are understandable and actionable. Dashboards enable employees to track key performance indicators, and identify areas for improvement, which suggests that performance outcomes may improve when employees engage with dashboards and make data-driven decisions (Almasi et al., 2023).

Drawing upon the theory of planned behaviour (Ajzen et al., 1980) and the Technology Acceptance Model (TAM), this article examines whether specific design characteristics influence the intention to use a risk communication dashboard. Despite numerous empirical studies on TAM extensions, few have investigated how dashboard design features, particularly visual and functional elements, act as antecedents of perceived usefulness (PU) and perceived ease of use (PEOU), especially in risk communication settings (Mlekus et al., 2020; Yigitbasioglu & Velcu, 2012; Sarikaya et al., 2018; Jiao & Cao, 2024). Existing dashboard studies largely focus on business intelligence, performance management systems or interactive visual analytics, leaving static awareness-oriented risk dashboards for SME users empirically underexamined. To address this gap, the present study makes three key contributions: (i) theoretically, it extends TAM3 to the underexplored domain of static risk communication dashboards; (ii) methodologically, it provides empirical evidence that three design features: Notifications and Alerts, Data Context, and Data-to-Ink Ratio, exert differentiated effects on PU and PEOU; (iii) analytically, it

incorporates user heterogeneity through Age and Education level within a TAM3-inspired framework, enabling a more nuanced understanding on how individual differences shape dashboard acceptance in SMEs.

This article is structured as follows: Section 2 reviews the technology acceptance models, the dashboards, the Partial Least Squares Structural Equation Modelling (PLS-SEM) approach, and the indicators associated with the TAM framework. Section 3 presents the proposed research model and hypotheses; Section 4 details the methodology; Section 5 reports the data analysis. Sections 6 to 8 discuss the results, the study's limitations and a conclusion.

2 Related Literature

2.1 Technology Acceptance Models

The Technology Acceptance Model (TAM) derives from the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975; Ajzen et al., 1980), and has become a foundational framework for understanding user adoption of new information technologies (Marangunic & Granic, 2015). TAM posits that perceived usefulness (PU) and perceived ease of use (PEOU) shape users' attitudes and intentions toward technology use. PU reflects the belief that technology enhances job performance, while PEOU refers to the belief that using it requires minimal effort. TAM has been validated across various technologies, including ERP systems, e-books, smartwatches, e-payment solutions, driving assistance systems, and data visualization tools (Daradkeh, 2017; Heikkila et al., 2018; Janes et al., 2013). To improve its predictive power, TAM2 introduced three additional social influence constructs (subjective norm, voluntariness, and image) and four cognitive instrumental processes (job relevance, output quality, result demonstrability, and perceived ease of use) (Venkatesh & Davis, 2000). Building on TAM2, the Unified Theory of Acceptance and Use of Technology (UTAUT) integrated elements from eight prior theories and identified four key predictors of behavioural intention: performance expectancy, effort expectancy, social influence and facilitating conditions; moderated by gender, age, experience, and voluntariness of use (Venkatesh et al., 2003). Subsequently, Venkatesh and Bala (2008) introduced TAM3, an integrated model identifying four antecedents of PU and PEOU: individual differences, system characteristics, social influence, and facilitating conditions. Recent research encourages examining design features as antecedents of PU and PEOU to foster user acceptance

of information technologies (Atarodi et al., 2019; Maruping et al., 2017; Venkatesh & Bala, 2008), as well as the impact of moderators such as age and education level on technology adoption (Venkatesh, 2022; Maruping et al., 2017; Ghouri & Mani, 2019). In this study, TAM is preferred over UTAUT due to its relative simplicity, strong predictive capabilities and broader applicability (Oviedo-Trespalacios et al., 2020; Rahman et al., 2017; Scherer et al., 2019; Janes et al., 2013; Ammenwerth, 2019). Empirical evidence consistently highlights PU as a strong driver of usage intention, while PEOU shows more variable effects across studies. A deeper understanding of the determinants of both perceived usefulness and perceived ease of use is essential for designing risk communication dashboards that promote user acceptance and usage among SME employees (Rahman et al., 2017; Vasnier et al., 2020).

2.2 The PLS-SEM approach

Partial Least Squares Structural Equation Modelling (PLS-SEM) is a robust statistical technique for exploring relationships between latent variables and their indicators (Wong, 2013). It is particularly suited for predictive modelling and theory development, making it a preferred approach for analysing frameworks like the Technology Acceptance Model (TAM) (Hair et al., 2019). PLS-SEM is widely applied across disciplines such as marketing, social sciences, and information systems. The method distinguishes between measurement models (linking indicators to constructs) and structural models (linking constructs to each other), with constructs classified as either reflective (indicators reflect the construct) or formative (indicators form the construct) (Mourre, 2013; Henseler et al., 2016). Researchers often select PLS-SEM over covariance-based SEM when dealing with small sample sizes, formative constructs, or exploratory research (Hair J. et al., 2021). This study employs both the standard PLS-SEM and the Consistent PLS-SEM (PLSc-SEM) algorithms to address concerns about composite-based SEM (Ronkko & Evermann, 2013) and to align results with factor-based models (Dijkstra & Henseler, 2015; Dash & Paul, 2021). Unlike covariance SEM, PLS-SEM does not provide a global model fit index such as Chi-square (χ^2). Instead, it uses alternative fit measures such as SRMR (Standardized Root Mean Square Residual), NFI (Bentler-Bonett normed fit index), d_ULS, and d_G to assess model adequacy. Overall, PLS-SEM offers a flexible and predictive approach for modelling complex variable relationships, especially in contexts where traditional SEM may be limited.

2.3 Dashboard

The term dashboard originates from the vehicle dashboard, which serves as a metaphor for providing a concise overview of system status to support timely action. In contemporary organisational contexts, dashboards are defined as graphical interfaces that enable employees and managers to monitor processes, identify trends, and detect anomalies (Pauwels K. et al., 2009). Dashboards support several core functions, including monitoring key performance indicators, triggering alerts when deviations occur, facilitating problem diagnosis through trend analysis, supporting data-driven decision-making, and guiding organisational performance (Eckerson, 2011). In SMEs, dashboards offer multiple benefits, such as streamlining repetitive tasks, enhancing transparency, instigating behavioural change, promoting continuous improvement, reducing organisational silos, and encouraging shared responsibility (Tezel et al., 2016). Dashboards can be broadly categorised by their intended use: strategic, tactical, or operational (Bititci et al., 2015).

Effective dashboards require a synergy of robust functional capabilities and thoughtful visual design (Few, 2006; Sarikaya et al., 2018). Functional features empower users to interact with and act on data, while visual characteristics ensure information is clear, accessible, and actionable. Table 1 summarizes key design features identified in the literature (Abduldaem & Gravell, 2019; Brandy et al., 2017; Rahman et al., 2017; Yigitbasioglu & Velcu, 2012; Vázquez-Ingelmo et al., 2019; Rabiei & Almasi, 2022).

Table 1: Summary of dashboard design features

Functional features	**Visual features**
Format flexibility and interactivity	Display information on a single page
Scenario analysis	High data-to-ink-ratio
Real-time notifications and alerts	Use of grid lines for 2D graphs
Format type (graph vs table)	Frugal use of colours
Top-down analysis capability	Improve the data context

2.4 Predictors and moderators associated with the model

To conduct an exhaustive statistical analysis of correlations within the structural model, the indicators for each construct in the Technology Acceptance Model (TAM) were derived from an extensive review of the literature (Davis et al., 1989; Scholtz et al., 2016; Surendran, 2012). Table 2 presents the indicators and corresponding declarative statements for the four main TAM

constructs: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Towards Usage (ATU), and Behavioural Intention to Use (BIU). Each indicator was operationalised as a declarative statement and assessed using a Likert-type scale, capturing respondents' level of agreement with each item.

Table 2: Constructs and Indicators

Construct	Indicator	Declarative statement
Perceived Usefulness (PU)	PU1	This visual representation effectively communicates threats and opportunities
	PU2	This visual representation supports collaboration between employees
	PU3	This visual representation helps reduce misunderstandings between management and employees
	PU4	This visual representation enhances the efficiency of employees' work
	PU5	Overall, this visual representation is useful for my work
Perceived Ease of Use (PEOU)	PEOU1	This visual representation is easy to interpret
	PEOU2	Interacting with this visual representation is simple and clear
	PEOU3	Learning to use this visual representation is easy for me
	PEOU4	Using this visual representation requires little mental effort
	PEOU5	Overall, this visual representation is easy to use
Attitude Towards Usage (ATU)	ATU1	I have a positive attitude toward using this visual representation
	ATU2	Using this visual representation in my company would be a good idea
	ATU3	Overall, I like the idea of using this visual representation
	ATU4	I find the use of this visual representation appealing
Behavioural Intention to Use (BIU)	BIU1	I intend to use this visual representation in the future
	BIU2	I intend to use this visual representation as frequently as possible
	BIU3	I would recommend the use of this visual representation to my colleagues
	BIU4	If this visual representation were available in my company, I would rely on it to adjust my priorities

While Table 1 lists the design features of a generic dashboard, our study focuses on a static risk communication dashboard intended for general awareness. A static dashboard, as defined by Bach et al. (2022), is characterised as a static (no-interaction), single page, screen-fit display of information. It typically contains concise representations such as single values, small charts and indicators. Accordingly, advanced functionalities such as scenario analysis,

interactivity and top-down analysis capability are excluded as they are not relevant in the context of a general-awareness risk dashboard (Sarikaya et al., 2018; Yigitbasioglu & Velcu, 2012; Nadj et al., 2020). To better understand the impact of some specific design features on the communication of risks in a SME context, we concentrated our literature review on the health sector which is highly advance in this area. According to the literature, focusing on notifications and alerts, contextual visualization, and a high data-ink ratio as design levers is particularly pertinent when targeting non-expert users, as these features directly address cognitive limitations and sense-making challenges identified in the information systems and visualization literature (Bach et al., 2022; Schulze et al., 2023; Hjelle et al., 2024; Ruddro & Mohana, 2023). The following sections describe each feature and its impact on the two constructs PU and PEOU, as reported in the literature:

- *Notifications and alerts* (Functional): Systematic reviews of public-health dashboards report that users explicitly wish for interactive features such as notifications to support timely response and monitoring (Schulze et al., 2023; Rabiei & Almasi, 2022). These prompt corrective actions when readings deviate from predefined targets. Alerts may appear in various forms, including distinct colours, flashing signals, or even audio cues. For example, the traffic light system offers a simple and universally understood method for communicating risk messages (Dowding et al., 2015). Prior research supports the hypothesis that dashboard reviews report alerts and reminders as core functional requirements to support timely response and task performance, which underpins Perceived Usefulness in operational settings (Zhuang et al., 2022; Chien et al., 2025)
- *The context of the data* (Visual): Public- health dashboard reviews emphasise that maps, diagrams and other visual elements, together with thoughtful colour use, are central to making risks understandable to non-expert users. Providing contextualised visualisations (graphs, annotations, pictograms) is therefore pertinent as it reduces cognitive effort, supports comprehension and causal analysis (Elias, 2012; Schulze et al., 2023; Hjelle et al., 2024). The literature supports the hypothesis that contextual visualization increases PEOU by making displays easier to interpret and reducing cognitive effort (Hjelle et al., 2024; Li et al., 2023)
- *Data-to-Ink Ratio* (Visual): Following Tufte's principle (Tufte E. , 2001), this ratio represents the proportion of ink used to display actual data compared to the total ink used in the entire display. The objective is to eliminate any ink that does not contribute to display data

effectively, allowing the remaining ink to be emphasised using saturated colours (Few, 2006). Visualisation and dashboard design work stresses the need to reduce unnecessary decorative elements and manage information density to avoid cognitive overload and improve perceptual effectiveness (Bach et al., 2022; Akter & Kudapa, 2024). Furthermore, this feature strengthens inclusivity, by considering accessibility for colour-blind users who perceive only two dominant colours (green and blue, red and blue, red and green) or shades of grey, constituting about 8% of the male population (Lanthony, 2005). The literature suggests the hypothesis that data-ink ratio should be better modelled as a contextual moderator rather than a simple positive predictor of PU and PEOU (Perkhofer et al., 2020; McGurgan et al., 2021). Table 3 summarises the indicators used for these three design features.

Table 3: Constructs and Indicators of the selected design characteristics

Construct	Indicator	Declarative statement
Notifications and Alerts (FF)	FF1	The scores are prioritised in a way that reflects their relative importance
	FF2	Each score is effectively reinforced by visual cues
Data Context (VF)	VF1	The dashboard provides clear explanations for higher or lower score (opportunity or threat)
	VF2	The scoring scale is consistently defined and easy to interpret
Data-to-ink Ratio (IR)	IR1	Each analysis result is expressed using a consistent format (e.g., number, letter, or symbol)
	IR2	The dashboard remains self-explanatory when displayed in greyscale

Finally, inspired by TAM3, which highlights individual differences (e.g., age, cultural background, personality, education) as important external variables and potential moderators of technology acceptance, we hypothesise that Education level acts as an antecedent (predictor) of PU and PEOU, while Age moderates key relationships in the model (e.g., between PU/PEOU and intention) (Blut et al., 2021; Liew et al., 2014; Hauk et al., 2018; Padilla-Meléndez et al., 2013).

3 Proposed Research Model and Hypotheses

Within the scope of a risk communication dashboard, this section presents the research model designed to analyse the impact of three exogenous constructs, namely "Notifications and Alerts," "Data Context," and “Education level”, on four endogenous latent constructs: PU, PEOU, ATU,

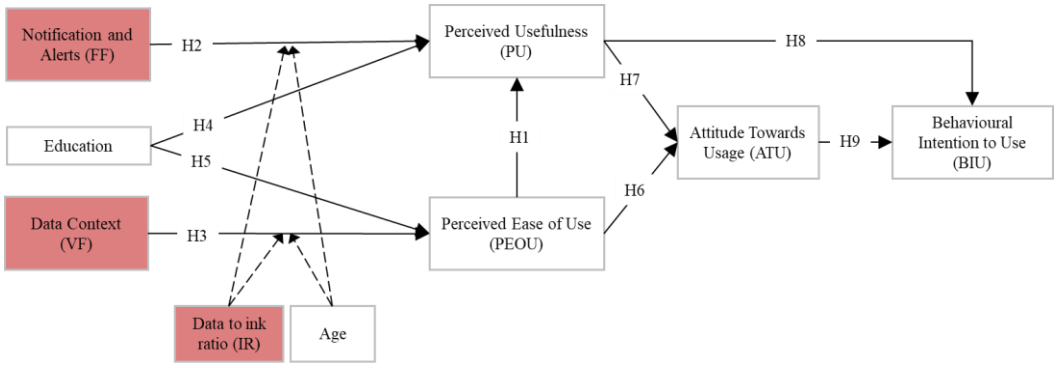
and BIU. Although dashboards can incorporate a wide range of visual and functional attributes, this study deliberately focuses on Notifications and Alerts and Data Context. This choice is theoretically motivated by the study's emphasis on static, awareness-oriented risk communication dashboards intended for SME users. Prior research indicates that in such contexts, cognitive salience and interpretability are more critical than advanced interactivity or analytical depth. Notifications and Alerts directly support timely attention and action, while Data Context facilitates sense-making under uncertainty. Other design features (e.g., drill-down, scenario analysis) are more relevant for expert, exploratory analytics and were therefore excluded to preserve model parsimony and internal validity."

Consistent with existing literature, we anticipate a positive effect between PEOU and PU, as greater ease of use is expected to enhance efficiency and foster collaboration among users. Previous studies have shown that both PEOU and PU are influenced by external variables, underscoring the importance of understanding these factors to explain individual technology adoption (Legris et al., 2003). Accordingly, we anticipate a direct influence of "Notifications and Alerts" on PU and "Data Context" on PEOU (Kesharwani & Singh Bisht, 2012; Venkatesh & Bala, 2008). Education level emerges as a critical determinant of organisational behaviour and technology acceptance, and should not be considered as a mere moderator (Petter et al., 2013; Abu-Shanab, 2021). We therefore expect "Education level" to influence the latent variables PU and PEOU (see Fig. 1). Additionally, "Data-to-ink ratio" (Tufte E. , 2013) and Age (Yousafzai et al., 2007) are introduced as moderators, affecting the strength of the relationship between the selected design characteristics and the pair PU / PEOU. Aligned with TAM, users who perceive a technology as useful are likely to experience improved performance and efficiency while prior research has identified PEOU as an unstable predictor of system acceptance (Abdekhoda et al., 2014). Also, we formulate hypotheses asserting that PEOU and PU positively influence ATU, and that PU positively influences employees' intention to use the risk communication board (Turner et al., 2010). Finally, we hypothesise that ATU directly influences the intention to use the dashboard (Davis et al., 1989). The conceptual model and nine hypotheses are illustrated in Fig. 1.

To enhance robustness and interpretability, we adopt a parsimonious model centered on theoretically essential TAM/TAM3 relationships, while treating additional paths as exploratory.

Moderation effects of Age and Data- to- Ink Ratio are analysed separately to avoid over- parameterisation.

Figure 1: Research model



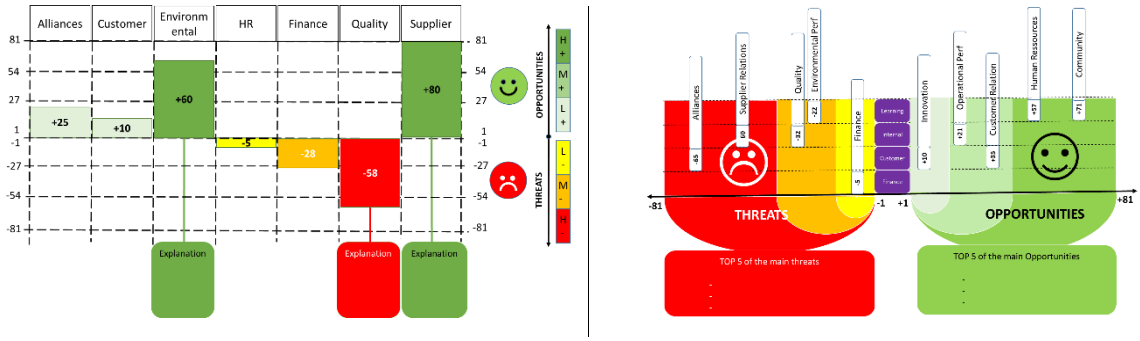
4 Methodology

4.1 Design of risk communication dashboards

Drawing on prior research on strategic dashboards (Vasnier et al., 2020), a collaborative brainstorming session was conducted with 14 mature students enrolled in a Master of Engineering (MEng) program (86% male, 14% female), with a mean age of 37 years ($\sigma \approx 7.5$ years). The objective was to design two dashboards that best align with the constructs: "Notifications and Alerts" and "Data Context."

Figure 2: The proposed Risk Communication Dashboards

Dashboard 1	Dashboard 2



Each dashboard (refer to Fig. 2) incorporates four key elements: i) the presentation of risk analysis scores across various performance dimensions; ii) the identification of positive scores by a green colour and the term "Opportunities," while negative scores are represented by a red colour and labelled "Threats"; iii) the reinforcement of the context through annotations in the lower section of the table; iv) the inclusion of a greyscale representation to ensure clarity for individuals with colour vision deficiencies.

4.2 Survey of experts

To explore individuals' attitudes and intentions towards using the proposed risk communication dashboards, an online survey was conducted targeting executives from Small and Medium-sized Enterprises (SMEs) (n = 210), who were concurrently enrolled in university courses. The survey achieved a response rate of 32% (n = 67), with an average age of 33 years ($\sigma \approx 7.5$ years), Table 4 presents the frequency and percentage distributions of the respondents' profile. To mitigate potential bias related to conflicts of interest, participants were deliberately selected from diverse professional backgrounds. Using executive students as proxies for company managers was deemed appropriate for evaluating the dashboards (King & He, 2006), given the inherent difficulty of engaging busy executives to dedicate time to respond to an online survey (Katok, 2011). Since these professionals were already familiar with using dashboards for decision-making or as simple bulletin boards, no additional training was required. In order to measure the degree of agreement or disagreement of the respondents, a Likert scale with seven response options is used. Level 1 corresponds to "strongly disagree" and 7 to "strongly agree", with a higher score indicating greater confidence in the factor. The questionnaire underwent a pre-test by academic colleagues to evaluate its readability, structure, and completion time. Minor adjustments, such as rewording, were made, and a short video was included to clarify the study's objectives, the fundamentals of the TAM model, and the scoring system.

Table 4: Respondents' profile

Demographic		Percent	N
Gender	Female	22%	52
	Male	78%	15
Age (years)	21-30	49%	33
	31-40	30%	20
	51-60	15%	10
	>60	6%	4
Work Experience	1 – 5 years	39%	26
	6 – 15 years	36%	24
	16 – 30 years	22%	15
	> 30 years	3%	2
Education level	level 4	3%	2
	level 5	16%	11
	level 6	25%	17
	level 7	52%	35
	level 8	3%	2

4.3 Sample size

To determine a representative sample size for a population of employees, a power analysis was conducted, considering the model's structure, the anticipated risk of error (α), and the expected effect size (f^2) (Marcoulides & Chin, 2013). GPower 3.1 was utilized for this analysis, selecting the statistical test "linear multiple regression: fixed model, single regression coefficient" (Faul et al., 2009) with the specified values: $f^2 = 0.15$ (moderate effect) (Cohen, 2013), $\alpha = 0.05$, number of predictors = 2 and a statistical power of 80% (Wong, 2013). The calculated minimum sample size was set at $n_{theoretical} = 55$. Since the actual number of respondents (n = 67) exceeds this theoretical minimum, the statistical analysis proceeded using the predictive nature of PLS-SEM (Shmueli et al., 2016). All metrics and methods for the analysis and result reporting follow the procedure recommended by (Hair et al., 2019).

5 Data analysis

The data obtained from the online survey underwent analysis using SmartPLS version 4.0. Following the guidelines proposed by (Chin, 2010), Bootstrap sampling (with a size 5000) was employed to assess the significance levels of formative indicators, reflective indicators, and regression coefficients between each factor. To address any concerns regarding the use of PLS,

the analysis was conducted using both the standard PLS-SEM algorithm and the Consistent PLS-SEM (PLSc-SEM) algorithm, the latter being recognized for producing results closely aligned with those of covariance-based SEM.

5.1 Measurement model (or external model)

Within the structural equations modelling framework employing the PLS method, a three-step procedure is mandated to evaluate the measurement model (Esposito-Vinzi et al., 2010): (i) the assessment of internal consistency, (ii) the convergent validity of the measures linked to the constructs, and (iii) the discriminant validity. In this case study, all factors are modelled as reflective constructs, except for the selected design factors: Notifications and Alerts (FF), Data Context (VF), and Data-to-Ink ratio (IR), which are treated as formative constructs (see Table 3).

- ***Assessing the external weight of reflective constructs***

To evaluate the external weight of reflective constructs, descriptive statistics for each indicator are presented in Table 5. The minimum outer loading observed is 0.791, which exceeds the recommended threshold of 0.708 (Hair et al., 2019). These loading values indicate that each construct explain more than 50% of the variance in its associated indicators.

Table 5: Descriptive Statistics of the Constructs

Indicators	PLS-SEM				PLSc-SEM (Consistent)			
	Outer loadings	CR	α	AVE	Outer loadings	CR	α	AVE
PU1	0.800				0.898			
PU2	0.850				0.675			
PU3	0.898	0.921	0.903	0.719	0.796	0.920	0.903	0.646
PU4	**0.791**				0.615			
PU5	0.896				0.978			
PEOU1	0.937				0.969			
PEOU2	0.944				0.917			
PEOU3	0.951	0.963	0.953	0.844	0.943	0.963	0.953	0.811
PEOU4	0.799				0.698			
PEOU5	0.953				0.948			
ATU1	0.936				0.901			
ATU2	0.937	0.961	0.960	0.894	0.937	0.961	0.960	0.859
ATU3	0.963				0.941			
ATU4	0.945				0.928			

BIU1	0.920	0.937	0.933	0.833	0.879	0.937	0.933	0.778
BIU2	0.919				0.819			
BIU3	0.936				0.965			
BIU4	0.873				0.858			

To assess the reliability and validity of the measurement model, composite reliability (CR) was calculated for the four reflective constructs, serving as an indicator of convergent reliability. CR values between 0.70 and 0.95 indicate a satisfactory to good level of reliability (Hair et al., 2011). In this study, all indicators exhibit high loadings on their respective latent variables, confirming strong reliability. Cronbach's alpha (α) values further support internal consistency, classified as 'good' across all constructs. Convergent validity was evaluated using the Average Variance Extracted (AVE), with all constructs exceeding the recommended threshold of 0.50, indicating that each construct explains at least 50% of the variance in its indicators (Fornell & Larcker, 1981). Finally, discriminant validity was examined to ensure that each indicator correlates more strongly with its own construct than with other latent variables (see Table 6).

Table 6: Discriminant validity of constructs (Note: The diagonal represents the square root of AVE and the other entries represent the square of the correlations**)**

	PLS-SEM				PLSc-SEM (Consistent)			
	ATU	BIU	PEOU	PU	ATU	BIU	PEOU	PU
ATU	**0.945**				**0.927**			
BIU	0.863	**0.912**			0.910	**0.882**		
PEOU	0.227	0.162	**0.919**		0.236	0.171	**0.901**	
PU	0.342	0.301	0.707	**0.848**	0.364	0.324	0.751	**0.804**

- ***Assessing the external weight of formative constructs***

The formative indicators are assessed based on three criteria: collinearity, significance, and reliability of indicators' weights. The Variance Inflation Factor (VIF) for each indicator of the two formative constructs, FF and VF (see Table 7), is below the threshold of 3 (Becker et al., 2015), with an average VIF of 1.071, slightly above 1.0 (Chatterjee & Price, 1991). This confirms the absence of multicollinearity among the formative indicators. Since PLS-SEM is a non-parametric method, bootstrapping was applied to evaluate the significance and reliability of each indicator. The t-values for both external weights and external loadings exceed 1.96, indicating that all indicators are statistically significant and can be retained for further analysis (Hair J. et

al., 2017). In addition, each external weight value falls between 0.2 and 1.0 (Chin, 1998), and the expected signs align with expectations, affirming that the reliability conditions are satisfied. Therefore, the validity and reliability of the measurement model are established.

Table 7: Co-linearity, Significance and Reliability of Formative Constructs (PLS-SEM and PLSc-SEM algorithms)

Indicators	Outer weights	t-value	*p*-value	Outer loadings	t-value	*p*-value	VIF
FF1	0.564	4.112	0.000	0.766	7.577	0.000	1.099
FF2	0.674	5.352	0.000	0.843	8.901	0.000	1.099
VF1	0.396	3.915	0.000	0.613	6.965	0.000	1.076
VF2	0.819	12.404	0.000	0.924	20.430	0.000	1.076
IR1	0.879	12.265	0.000	0.944	18.637	0.000	1.038
IR2	0.337	2.308	0.021	0.505	3.903	0.000	1.038

5.2 Structural model (or internal model)

After confirming the validity of the measurement model, the next step is to evaluate the structural model, which involves assessing the predictive relevance of the model and the relationships among constructs. Several criteria, such as the coefficient of determination (R^2), regression coefficients (β) and their significance and model fit indices, are considered.

- **Measuring the coefficient of determination (R^2)**

The coefficient of determination (R^2) is a widely used metric for assessing the predictive power of a structural model, representing the cumulative effects of all linked exogenous constructs on an endogenous construct. To reduce bias towards a complex model, the adjusted coefficient of determination (R^2 adjusted) is also considered (Hair J. et al., 2017). In this study, the R^2 values for the four constructs (PEOU, PU, ATU, and BIU) range from 0.180 to 0.827 (see Table 8). Specifically, BIU exhibits a strong effect size, PU shows a moderate effect, while PEOU and ATU display low to weak effect sizes. These findings are consistent with prior studies (excluding ATU), which indicates that TAM typically explains around 40% of the variance in constructs such as PU, PEOU, ATU, and BIU when applied to information technologies (Atarodi et al., 2019).

Table 8: R^2 values

	PLS-SEM	PLSc-SEM (Consistent)	Assumption

	R^2	R^2 adjusted	R^2	R^2 adjusted	
ATU	0.229	**0.180**	0.266	0.219	Weak
BIU	0.745	0.739	**0.827**	0.824	Strong
PEOU	0.451	0.409	0.468	0.428	Low
PU	0.655	0.525	0.730	0.706	Moderate

Note: Weak: $R^2 < 0.25$; Low: $R^2 < 0.25 – 0.5 >$; Moderate: $R^2 < 0.5 – 0.7 >$; Strong: $R^2 > 0.7$ (Henseler et al., 2009) (Hair et al., 2011)

- **Relationship among constructs**

The β-values for each path in the structural model were computed. The significance of each β-value was tested using the t-test statistic, with bootstrap sampling (with a sample size of 5000) applied to evaluate the hypotheses (see Table 9). The p-value represents the probability of obtaining a test statistic equal to or greater than the observed result under the null hypothesis (H0: β=0) (Stern, 2016). A p-value below 0.05 provides sufficient evidence to reject the null hypothesis.

Of the nine hypotheses, six find statistical support, confirming strong relationships in the expected direction of the research model. Both algorithms produced similar β-coefficients and p-values. The influence of Attitude Towards Usage (ATU) on employees' intention to use a risk communication dashboard was substantial, as confirmed by hypothesis H9 (β = 0.861, p value < 0.001). Perceived Usefulness (PU) positively affected ATU (β = 0.361, p value < 0.05), validating hypothesis H7. PU is strongly influenced by Perceived Ease of Use (PEOU) (β = 0.549, p value < 0.001). As anticipated, PEOU has an insignificant effect on ATU (β = -0.030, p value > 0.05). Surprisingly, PU plays a negligeable role in predicting Behavioural Intention (BI) (β = 0.007, p value > 0.05). As hypothesized, Notifications and Alerts (FF) significantly influenced PU (β = 0.362, p value < 0.001), and Data Context (VF) strongly affected PEOU (β = 0.680, p value < 0.001). Finally, Education level negatively impacted PU (β = -0.194, p value < 0.05), but had no significant effect on PEOU (β = 0.072, p value > 0.05).

Table 9: Hypotheses Test Results

Hypothesis	Relation	PLS-SEM		PLSc-SEM (Consistent)		Supported?
		Path coefficient (β)	*p*-value	Path coefficient (β)	*p*-value	
H1	PEOU → PU	0.549	0.000	0.606	0.000	Yes
H2	FF → PU	0.362	0.000	0.389	0.000	Yes

H3	VF → PEOU	0.680	0.000	0.707	0.000	Yes
H4	Education → PU	-0.194	0.011	-0.201	0.010	Yes
H5	Education → PEOU	0.072	0.320	0.077	0.320	No
H6	PEOU → ATU	-0.030	0.885	-0.082	0.685	No
H7	PU → ATU	0.361	0.017	0.424	0.024	Yes
H8	PU → BIU	0.007	0.904	-0.008	0.873	No
H9	ATU → BIU	0.861	0.000	0.912	0.000	Yes

- **Model fit indices**

Model fit indices were computed for both the saturated model, which evaluates correlations among all constructs, and the estimated model, which represents a more constrained structure based on total effects. The Standardised Root Mean Square Residual (SRMR) indicates the average standardised residuals between observed and predicted covariance matrices (Chenn, 2007). An SRMR value of ≤ 0.08 suggests a well-fitted model (Hu & Bentler, 1998), and in this study, SRMR values range from 0.061 to 0.080 (Table 10), indicating a good fit. The Bentler-Bonett Normed Fit Index (NFI), which ranges from 0 to 1 (with 1 being ideal), also assess the model fit. A threshold of 0.90 indicates a good fit; however, our NFI values fall between 0.768 and 0.803, suggesting a somewhat compromised fit (Sarmento & Costa, 2019), bearing in mind that NFI is sensitive to sample size. Additionally, the bootstrap-based test for the exact overall model fit evaluates the discrepancy between the empirical covariance matrix and the matrix implied by the composite factor model. Following (Dijkstra & Henseler, 2015), two metrics: d_ULS (squared Euclidean distance) and d_G (geodesic distance) were examined. For both the saturated and estimated models, the values of d_ULS and d_G fall within the upper bound of the 99% confidence intervals, indicating that the model demonstrates an acceptable overall fit.

Table 10: Model fit indices

	PLS-SEM							
	Saturated model	Sample Mean	95%	99%	Estimated model	Sample Mean	95%	99%
SRMR	0.067				**0.080**			
d_ULS	1.322	0.917	1.509	1.898	1.936	1.081	1.733	2.200
d_G	1.003	0.719	1.008	1.162	1.020	0.731	1.026	1.187
NFI	**0.803**				0.800			
	PLSc-SEM (Consistent)							
	Saturated model	Sample Mean	95%	99%	Estimated model	Sample Mean	95%	99%
SRMR	**0.061**				0.074			

d_ULS	1.119	0.933	1.550	2.023	1.632	1.078	1.740	2.214
d_G	1.252	n/a	n/a	n/a	1.267	n/a	2.489	n/a
NFI	0.771				**0.768**			

5.3 Moderators effect assessment

Table 11 presents the significance of the indirect effects among the constructs of the research model. Consistent with prior literature, Age exerts a moderate positive indirect effect on PU through Notifications and Alerts (FF) (β = 0.155, p value < 0.05). In contrast, it has no significant effect on PEOU via the construct Data Context (VF) (β = 0.069, p value > 0.05). Similarly, the indirect effect of "Data-to-ink ratio" (IR) on PU through FF (β = 0.064, p value > 0.05) is unsupported. Nonetheless, IR exhibits a weak but positive effect on PEOU through VF (β = 0.124, p value < 0.05).

Table 11: Moderators effects assessment

Relation	PLS-SEM		PLSc-SEM (Consistent)		Supported?
	Path co-efficient (β)	*p*-value	Path co-efficient (β)	*p*-value	
IR x VF → PEOU	0.124	0.035	0.126	0.035	Yes
IR x FF → PU	0.064	0.466	0.049	0.481	No
Age x FF → PU	0.155	0.024	0.180	0.024	Yes
Age x VF → PEOU	0.069	0.387	0.078	0.387	No

6 Discussion

The primary objective of this case study was to evaluate the applicability of the Technology Acceptance Model (TAM) within the context of risk communication dashboards, focusing on the interactions among seven core constructs (Education, Notifications and Alerts (FF), Data Context (VF), PU, PEOU, ATU, BIU) and two moderators (Age, Data-to-ink ratio (IR)). With a sample size exceeding the theoretical threshold (n = 67), the study adopted a composite-based SEM approach as a prediction-oriented method. To address criticisms regarding PLS-SEM's inability to control measurement errors (Ronkko & Evermann, 2013), PLSc-SEM was used as an alternative method to strengthen analytical rigour (Manosuthi et al., 2021). The assessment of the reflective constructs (PU, PEOU, ATU and BIU) demonstrated robust support: indicators exhibited high loadings on their respective constructs, internal consistency was satisfactory, constructs explained at least 50% of indicator variance, and discriminant validity was confirmed.

For the formative constructs (FF, VF), no multicollinearity issues were detected, supporting their reliability and significance. Model fit indices indicated moderate but acceptable predictive power, offering valuable insights into the relationships between the studied constructs. Overall, this research extends TAM's application in the field of static risk communication dashboards. The findings confirm the model's reliability and validity, while highlighting nuanced interactions between the dashboard design features and the traditional TAM3 constructs and moderators. These results provide a foundation for further research and practical guidance for implementing TAM in risk communication contexts.

6.1 Theoretical implications

At a macro level, the study supports TAM's validity and relevance for risk communication dashboards. The key findings are summarized below:

- **H1:** The strong positive effect of PEOU on PU is consistent with prior research, confirming that ease of use enhances perceived usefulness (Legris et al., 2003; Hess et al., 2014).
- **H2:** The moderate and positive effect of Notifications and Alerts (FF) on PU underscores the importance of functional features in explaining over 60% of PU variance (Pauwels K. et al., 2009), consistent with findings in online retailing (Yang et al., 2016; Kim & Sim, 2012).
- **H3:** The moderate positive effect of Data Context (VF) on PEOU is consistent with prior visualisation and dashboard research. Contextualised and highlighted data are easier to perceive and understand, while well-structured, visually cued dashboards reduce cognitive load and direct users' attention to relevant information (Li et al., 2023; Vasnier et al., 2020; Kahn, 2017; Milosavljevic et al., 2012).
- **H4:** Consistent with prior research that treats education level as a moderating individual difference in TAM models, our results show a negative effect of education on perceived usefulness: high-school respondents rate dashboards as more useful than graduates. This finding may be interpreted as an expectation–fit effect: higher educated users demand more sophisticated analytics and thus evaluate the same dashboards as less useful, whereas lower educated users experience a larger relative benefit from the basic feedback provided (Rets et al., 2021; Ramaswami et al., 2023)

- **H5:** Education level had a small and statistically non-significant effect on PEOU, suggesting that formal education does not meaningfully shape users' ease of interacting with the dashboards. This aligns with prior TAM research where PEOU is primarily determined by technology-related factors such as self-efficacy, enjoyment, experience, and system quality rather than demographic variables (Abdullah & Ward, 2016; Granić & Marangunić, 2019; Huang et al., 2022)
- **H6:** The absence of PEOU's effect on ATU, consistent with Facebook usage studies (Ramayah et al., 2017), may be attributed to the profile of the interviewees, which consists of SME executives. Meta-analytic and review work highlights that PU is typically the strongest predictor of attitude and intention, with PEOU's role more variable and often indirect via PU (Damerji & Salimi, 2021; Malatji et al., 2020). Given that our sample comprises educated executives e.g. experienced technology users and performance-oriented decision-makers, it is reasonable that they prioritise the tool's usefulness over its ease of use when forming attitudes, explaining the absence of a PEOU–ATU effect.
- **H7:** PU positively influences ATU, in line with the Technology Acceptance Model, where beliefs that a system enhances job or daily performance lead to more favourable attitudes and stronger adoption intentions (Lee et al., 2013).
- **H8:** The lack of support for the path between PU and BIU may result from conflicting user intentions, particularly between pioneers and non-adopters. Several studies involving students have documented non-significant PU-BIU relationships in context like mobile learning tool (Park et al., 2012), transportation apps or the usage of Moodle (Sanchez & Hueros, 2010).
- **H9:** Attitude remains the strongest predictor of BIU (Teo & Zhou, 2014), confirming that employees are more likely to adopt dashboards perceived as useful and well-designed.
- **Moderators:** Our findings justify modelling Age as an indirect driver of PU through specific interface features, such as well-designed notifications and alerts that are more salient or supportive for certain age groups. It confirms that demographic factors such as age, gender, education, experience and location significantly shape technology adoption (Abu-Shanab, 2021). In addition, the results support the idea that data-to-ink ratio influences PEOU indirectly via perceived data context (clarity, relevance,

interpretability), fitting the broader evidence that external, interface-level variables shape PEOU (McGurgan et al., 2021).

6.2 Managerial implications

As Pauwels et al. (2009) emphasise, a dashboard's purpose must align with its functional characteristics; misalignment can result in poor decisions or information lacking meaningful context. In the case of risk communication dashboards for SMEs, this study offers several practical recommendations:

- Ensure an intuitive design to reduce cognitive load, as Perceived Ease of Use (PEOU) strongly influences Perceived Usefulness (PU). Simple navigation and clear layouts are therefore essential to improving adoption.
- Strengthen Functional Features (FF) to enhance PU. Dashboards should include risk prioritisation mechanisms, numerical indicators, and alert systems to make information actionable.
- Leverage Visual Features (VF) to improve Ease of Use, especially under cognitive load. Incorporate global scales, explanatory legends, and narrative or storytelling elements to clarify high and low-risk scores.
- Address demographic differences, as age negatively moderates PU. Older employees may require tailored onboarding and additional support to ensure successful adoption.
- Highlight practical benefits during implementation, since PU predicts Attitude Toward Use (ATU). Emphasise how dashboards improve decision-making and reduce uncertainty to foster positive attitudes.

7 Limitations and Future Research

While this study sought to address multiple critical aspects of dashboard design and user acceptance, several limitations must be acknowledged. First, the proposed model does not fully capture all visual and functional attributes inherent in dashboards. Second, moderators such as gender and voluntariness of use, as suggested by the UTAUT framework, were not examined. Third, the sample size was relatively small, future studies should target larger samples (e.g. more than 200 respondents) to increase statistical power and enable multigroup analyses. Fourth, the research adopted a predictive rather than deterministic approach. Although new determinants (FF,

VF, Education) and moderators (Age and Data-to-ink ratio) were introduced to explain the variance of PU and PEOU, the analysis remains prospective rather than confirmatory. Finally, the analysis focused on two specific risk communication dashboards, extending the investigation to a broader range of dashboards would provide a more comprehensive understanding of design feature effects. The authors hope that these limitations guide subsequent research in the specialised domain of dashboards design and adoption.

8 Conclusion

Communicating risk analysis results to employees in a Small and Medium-sized Enterprise (SME) presents significant challenges, particularly in distinguishing between high and low risks. While risks are traditionally conveyed numerically, incorporating visual elements such as graphs, enhances comprehension and serves as an effective complement to numerical data. Despite the potential benefits, the influence of risk communication dashboards on risk perception, decision-making and user behaviour remains underexplored. This study addresses gaps identified in the literature (Berg et al., 2021; Mlekus et al., 2020; Jiao & Cao, 2024), by examining three design characteristics (Data-to-ink ratio, Notifications and alerts and Data context) that encompass both functional and visual aspects. These indicators provide a structured framework for evaluating dashboards based on their perceived usefulness and ease of use from the user's perspective. We extrapolate that well-designed risk communication dashboards can foster employee engagement, ultimately improving quality, productivity, and profitability (Yigitbasioglu & Velcu, 2012; Gueguen, 2010; Prasanna et al., 2019).

Data availability statement

The datasets presented in this article are not readily available, further inquiries can be directed to the corresponding author.

Declarations

All authors whose names appear on the submission

1) made substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data; or the creation of new software used in the work;

2) drafted the work or revised it critically for important intellectual content;

3) approved the version to be published; and

4) agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved;

5) did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors;

6) that the data sets generated during the current study are available from the corresponding author on reasonable request;

7) have no competing interests to declare that are relevant to the content of this article.

References

Abdekhoda, M., Ahmadi, M., Dehnad, A., & Hosseini, A. F. (2014). Information technology acceptance in health information management. *Methods of information in medicine, 53*(1), 14-20. https://doi.org/doi:10.3414/me13-01-0079

Abduldaem, A., & Gravell, A. (2019). Principles for the design and development of dashboards: A literature review. *Proceedings of INTCESS 2019 - 6th international conference on education and social sciences,* (pp. 1307-1311). Dubai.

Abdullah, F., & Ward, R. (2016). eveloping a General Extended Technology Acceptance Model for E-Learning (GETAMEL) by analysing commonly used external factors. *Computers in human behavior, 56,* 238-256.

Abu-Shanab, E. (2021). Demographic Factors as Determinants of E-Government Adoption. *In Recent Developments in Individual and Organizational Adoption of ICTs,* pp. 60-81.

Ajzen, I., Fishbein, M., & Robert, L. (1980). *Understanding attitudes and predicting social behavior.* Englewoods Cliffs, NJ: Prentice-hall.

Akter, M., & Kudapa, S. (2024). A comparative analysis of artificial intelligence-integrated bi dashboards for real-time decision support in operations. *International Journal of Scientific Interdisciplinary Research, 5*(2), 158-191.

Almasi, S., Bahaadinbeigy, K., Ahmadi, H., Sohrabei, S., & Rabiei, R. (2023). Usability Evaluation of Dashboards: A Systematic Literature Review of Tools. *BioMed Research International*.

Ammenwerth, E. (2019). Technology Acceptance Models in Health Informatics: TAN and UTAUT. *Applied Interdisciplinary Theory in Health Informatics, 263*, 64-71.

Atarodi, S., Berardi, A., & Toniolo, A. (2019). Le modèle d'acceptation des technologies depuis 1986: 30ans de développement. *Psychologie du travail et des organisations, 25*(3), 191-207. https://doi.org/doi:10.1016/j.pto.2018.08.001

Bach, B., Freeman, E., Abdul-Rahman, A., Turkay, C., Khan, S., Fan, Y., & Chen, M. (2022). Dashboard design patterns. *IEEE Transactions on Visualization and Computer Graphics, 29*(1), 342-352.

Becker, J. M., RIngle, C. M., Sarstedt, M., & Volckner, F. (2015). How collinearity affects mixture regression results. *Marketing letters, 26*(4), 643-659. https://doi.org/doi:10.1007/s11002-014-9299-9

Benoliel, P., & Somech, A. (2014). The health and performance effects of participative leadership: Exploring the moderating role of the Big Five personality dimensions. *European Journal of Work and Organizational Psychology, 23*(2), 277-294.

Berg, S., O'Hara, J., Shortt, M., Thune, H., Brønnick, K., & Lungu, D. (2021). Health authorities' health risk communication with the public during pandemics: a rapid scoping review. *BMC Public Health, 21:1401*.

Bititci, U., Cocca, P., & Ates, A. (2015). Impact of visual performance management systems on the performance management practices of organisations. *International Journal of Production Research, 54*(6), 1571-1593. https://doi.org/doi:10.1080/00207543.2015.1005770

Blut, M., Chong, A., Tsiga, Z., & Venkatesh, V. (2021). Meta-analysis of the unified theory of acceptance and use of technology (UTAUT): challenging its validity and charting A research agenda in the red ocean. *Journal of the Association for Information Systems, forthcoming.*

Brandy, A., Mantelet, F., Aoussat, A., & Pigot, P. (2017). Proposal for a new usability index for product design teams and general public. *Human behaviour in Design, 8,* 199-208.

Burton-Jones, A., & Hubona, G. (2005). Individual differences and usage behavior: revisiting a technology acceptance model assumption. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 36*(2), 58-77.

Chatterjee, S., & Price, B. (1991). *Regression Analysis by example* (2ème Edition ed.). New York: Wiley.

Chenn, F. F. (2007). Sensitivity of Goodness of Fit Indexes to Lack of Measurement Invariance. *Stuctural Equation Modelling: A multidisciplinary journal, 14*(3), 464-504. https://doi.org/doi:10.1080/10705510701301834

Chien, S., Chien, C., Chen, C., Chien, P., Hsu, C., Yang, H., & Li, Y. (2025). Using technology acceptance model to explore physicians' perspectives of clinical decision support system alerts. *BMJ Health & Care Informatics, 32*(1), e101128.

Chin, W. W. (1998). The Partial Least Squares Approach For Structural Equation Modeling. In *Modern Methods for Business Research* (pp. 295-336). Hillsdale, NJ: Lawrence erlbaum associates.

Chin, W. W. (2010). Bootstrap cross-validation indices for PLS path model assessment. (S. Handbooks, Ed.) *Handbook of Partial least squares*, pp. 83-97. https://doi.org/doi:10.1007/978-3-540-32827-8_4

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences.* Academic press.

Daradkeh, M. (2017). A preliminary study of user acceptance and adoption of data visualisation tools for decision support in business organisations. *International Journal of Business Information Systems, 26*(3), 297-317.

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change, 173*, 121092.

Davis, F., Bagozzi, R., & Warshaw, P. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982-1003. https://doi.org/https://doi.org/10.1287/mnsc.35.8.982

Dijkstra, T., & Henseler, J. (2015). Consistent Partial Least Squares Path Modeling. *MIS Quarterly, 39*(2), 297-316.

Dowding, D., Randell, R., Gardner, P., Fitzpatrick, G., Dykes, P., Favela, J., & Currie, L. (2015). Dashboards for improving patient care: review of the literature. *International journal of medical informatics, 84*(2), 87-100. https://doi.org/doi:10.1016/j.ijmedinf.2014.10.001

Eckerson, W. (2011). *Performance Dashboards: Measuring, Monitoring and Managing your business* (Vol. Second ed.). New Jersey: Wiley & Sons.

Elias, M. (2012). *Enhancing user interaction with business intelligene dashboards.* Paris: Ecole centrale.

Esposito-Vinzi, V., Trinchera, L., & Amato, S. (2010). PLS Path Modeling: From Foundations to Recent Developments and Open Issues for Model Assessment and Improvement. In *Handbook of Partial Least Squares: Concepts, Methods and Applications* (pp. 47-82). Heidelberg: Springer. https://doi.org/doi:10.1007/978-3-540-32827-8_3

Faul, F., Erdfelder, E., Buchner, A., & Lang, A. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior research methods, 41*(4), 1149-1160. https://doi.org/doi:10.3758/brm.41.4.1149

Few, S. (2006). *Information dashboard design: the effective visual communication of data.* O'Reilly Media.

Fishbein, M., & Ajzen, I. (1975). Attitude-behaviour relations: a theoretical analysis and review of emprirical research. *Psychological Bulletin, 84*, 888-918.

Fornell, C., & Larcker, D. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research, 18*(1), 39-50. http://dx.doi.org/10.2307/3151312

Ghouri, A., & Mani, V. (2019). Role of real-time information-sharing through SaaS: An industry 4.0 perspective. *International Journal of Information Management, 49*, 301-315.

Granić, A., & Marangunić, N. (2019). Technology acceptance model in educational context: A systematic literature review. *British Journal of Educational Technology, 50*(5), 2572-2593.

Gueguen, G. (2010). Persistance des caractéristiques initiales du dirigeant et croissance de la PME. *10ème Congrés International Francophone en Entrepreneuriat et PME, Bordeaux, France*( ).

Gueguen, G., Janssen, F., & Giacomin, O. (2016). Persistance dans le temps des déterminants de la croissance des PME. *Revue internationale P.M.E., 28*(3-4), 103-137. https://doi.org/doi:10.7202/1035412ar

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of marketing theory and practice, 19*(2), 139-152. https://doi.org/doi:10.2753/mtp1069-6679190202

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report te results of PLS-SEM. *European Business Review, 31*(1), 2-24. https://doi.org/doi:10.1108/ebr-11-2018-0203

Hair, J. F., Sarstedt, M., & Ringle, C. M. (2019). Rethinking some of the rethinking of partial least squares. *European journal of marketing*.

Hair, J., Hult, G., Ringle, C., & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM).* Thousand Oaks, CA: Sage.

Hair, J., Hult, G., RIngle, C., Sarstedt, M., Danks, N., & Ray, S. (2021). *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R* . Springer.

Hauk, N., Huffmeier, J., & Krumm, S. (2018). Ready to be a silver surfer? A meta-analysis on the relationship between chronological age and technology acceptance. *Computers in Human Behavior, 84*, 304-319.

Heikkila, P., Honka, A., & Kaasinen, E. (2018). Quantified factory worker: designing a worker feedback dashboard. *Proceedings of the 10th Nordic conference on Human-Computer Interaction, Oslo, Norway*, 515-523.

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling innew technology research: updated guidelines. *Industrial Management & Data System, 116*(1), 2-20.
Henseler, J., Ringle, C. M., & Sinkovics, R. R. (2009). The use of partial least squares path modeling in international marketing. In *Advances in International Marketing* (pp. 277-320). Bingley: Emerald.
Hess, T. J., McNab, A. L., & Basoglu, K. A. (2014). Reliability generalization of perceived ease of use, perceived usefulness, and behavioral intentions. *Mis Quarterly, 38*(1), 1-28.
Hjelle, S., Mikalef, P., Altwaijry, N., & Parida, V. (2024). Organizational decision making and analytics: An experimental study on dashboard visualizations. *Information & Management, 61*(6), 104011.
Hu, L., & Bentler, P. M. (1998). Fit Indices in Covariance Structure Modeling: Sensitivity to Underparameterized Model Misspecification. *Psychology Methods, 3*(4), 424-453. https://doi.org/doi:10.1037/1082-989x.3.4.424
Huang, F., Teo, T., & Scherer, R. (2022). Investigating the antecedents of university students' perceived ease of using the Internet for learning. *Interactive learning environments, 30*(6), 1060-1076.
Janes, A., Sillitti, A., & Succi, G. (2013). Effective dashboard design. *Cutter IT Journal, 26*(1), 17-24.
Jiao, J., & Cao, X. (2024). Research on designers' behavioral intention toward artificial Intelligence-Aided design: Integrating the theory of planned behavior and the technology acceptance model. *Frontiers in Psychology, 15*, 1450717.
Kahn, B. (2017). Using visual design to improve customer perceptions of online assortments. *Journal of retailing, 93*(1), 29-42.
Katok, E. (2011). Using laboratory experiments to build better operations management models. *Technology, information and operations management, 5*(1), 1-86. https://doi.org/doi:10.1561/9781601984951
Kesharwani, A., & Singh Bisht, S. (2012). Kesharwani, A.The impact of trust and perceived risk on internet banking adoption in India: An extension of technology acceptance model. *International journal of bank marketing, 30*(4), 303-322.
Kim, Y., & Sim, J. (2012). Acceptance-diffusion strategies for Tablet-PCs: focused on acceptance factors of non-users and satisfaction factors of users. *ETRI Journal, 34*, 245-255.
King, W., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & management, 43*(6), 740-755. https://doi.org/doi:10.1016/j.im.2006.05.003
Lai, V. S., & Li, H. (2005). Technology acceptance model for internet banking: an invariance analysis. *Information & Management, 42*(2), 373-386. https://doi.org/doi:10.1016/j.im.2004.01.007
Lanthony, P. (2005). *Daltonisme et activités humaines.* Maloine.
Lee, Y., Hsieh, Y., & Chen, Y. (2013). An investigation of employees' use of e-learning systems: Applying the technology acceptance model. *Behaviour & Information Technology, 32*(2), 173-189.
Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management, 40*(3), 191-204. https://doi.org/doi:10.1016/s0378-7206(01)00143-4
Li, G., Wang, L., & Hu, J. (2023). Integration with Visual Perception—Research on the Usability of a Data Visualization Interface Layout in Zero-Carbon Parks Based on Eye-Tracking Technology. *Sustainability, 15*(14), 11102.

Liew, E., Vaithilingam, S., & Nair, M. (2014). Facebook and socio-economic benefits in the developing world. *Behaviour & Information Technology, 33*(4), 345-360.
Manosuthi, N., Lee, J., & Han, H. (2021). An innovative application of composite-based structural equation modeling in hospitality research with empirical example. *Cornell Hospitality Quarterly, 62*(1), 139-156.
Marangunic, N., & Granic, A. (2015). Technology acceptance model: a literature review from 1986 to 2013. *Universal access in the information society, 14*, 81-95.
Marcoulides, G. A., & Chin, W. W. (2013). You write, but others read: common methodological misunderstandings in PLS and related methods. In *New Perspectives in Partial Least Squares and Related Methods* (pp. 31-64). New York: Springer.
Maruping, L., Bala, H., Venkatesh, V., & Brown, S. (2017). Going beyond intention: Integrating behavioral expectation into the unified theory of acceptance and use of technology. *Journal of the Association for Information Science and Technology, 68*(3), 623-637.
McGurgan, K., Fedoroksaya, E., Sutton, T., & Herbert, A. (2021). Graph Design: The Data-ink Ratio and Expert Users. *In VISIGRAPP (3: IVAPP)*, 188-194.
Milosavljevic, M., Navalpakkam, V., Koch, C., & Rangel, A. (2012). Relative Visual Salience Differences Induce Sizable Bias in Consumer Choice. *Journal of Consumer Psychology, 22*(1), 67-74.
Mlekus, L., Bentler, D., Paruzel, A., Kato-Beiderwieden, A., & Maier, G. (2020). How to raise technology acceptance: user experience characteristics as technology-inherent determinants. *Gruppe. Interaktion. Organisation. Zeitschrift für Angewandte Organisationspsychologie (GIO), 51*(3), 273-283.
Mourre, M.-L. (2013). *La modélisation par équations structurelles basée sur la méthode PLS : une approche intéressante pour la recherche en marketing.* Paris, France: Université Paris-Est Créteil.
Nadj, M., Maedche, A., & Schieder, C. (2020). The effect of interactive analytical dashboard features on situation awareness and task performance. *Decision support systems, 135*, 113322.
Oviedo-Trespalacios, O., Briant, O., Kaye, S. A., & King, M. (2020). Assessing driver acceptance of technology that reduces mobile phone use while driving: The case of mobile phone applications. *Accident Analysis & Prevention, 135*, 105348.
Padilla-Meléndez, A., Del Aguila-Obra, A., & Garrido-Moreno, A. (2013). Perceived playfulness, gender differences and technology acceptance model in a blended learning scenario. *Computers & Education, 63*, 306-317.
Park, S., Nam, M., & Cha, S. (2012). University students' behavioral intention to use mobile learning: Evaluating the technology acceptance model. *British journal of educational technology, 43*(4), 592-605.
Pauwels, K., Ambler, T., Bruce, H., Lapointe, P., Reibstein, D., & Skiera, B. (2009). Dashboards as a service: why, what, how, and what research is needed? *Journal of service research, 12*(2), 175-189. https://doi.org/doi:10.1177/1094670509344213
Perkhofer, L., Walchshofer, C., & Hofer, P. (2020). Does design matter when visualizing Big Data? An empirical study to investigate the effect of visualization type and interaction use. *Journal of Management Control, 31*(1-2), 55-95.
Petter, S., Delone, W., & McLean, E. (2013). Information systems success: The quest for the independent variables. *Journal of management information systems, 29*(4), 7-62.
Prasanna, R., Jayasundara, J., Naradda Gamage, S., Ekanayake, E., Rajapakshe, P., & Abeyrathne, G. (2019). Sustainability of SMEs in the competition: A systemic review on

technological challenges and SME performance. *Journal of Open Innovation: Technology, Market, and Complexity, 5*(4), 100.
Rabiei, R., & Almasi, S. (2022). Requirements and challenges of hospital dashboards: a systematic literature review. *BMC medical informatics and decision making, 22*(1), 287.
Rahman, A., Adamu, Y., & Harun, P. (2017). Review on dashboard application from managerial perspective. *2017 International Conference on Research and Innovation in Information Systems (ICRIIS)*. https://doi.org/doi:10.1109/icriis.2017.8002461
Rahman, M. M., Lesch, M. F., Horrey, W. J., & Strawderman, L. (2017). Assessing the utility of TAM, TPB, and UTAUT for advanced driver assistance systems. *Accident Analysis & Prevention, 108*, 361-373.
Ramaswami, G., Susnjak, T., & Mathrani, A. (2023). Effectiveness of a learning analytics dashboard for increasing student engagement levels. *Journal of Learning Analytics, 10*(3), 115-134.
Ramayah, T., Yeap, J., Ahmad, N., Halim, H., & Rahman, S. (2017). Testing a confirmatory model of facebook usage in SmartPLS using consistent PLS. *International journal of business and innovation, 3*(2), 1-14.
Rets, I., Herodotou, C., Bayer, V., Hlosta, M., & Rienties, B. (2021). Exploring critical factors of the perceived usefulness of a learning analytics dashboard for distance university students. *International Journal of Educational Technology in Higher Education, 18*(1), 46.
Ronkko, M., & Evermann, J. (2013). A critical examination of common beliefs about partial least squares path modeling. *Organizational Research Methods, 16*(3), 425-448.
Ruddro, R., & Mohana, H. (2023). Visual communication in industrial safety systems: a review of UI/UX design for risk alerts and warnings. *American Journal of Scholarly Research and Innovation, 2*(02), 217-245.
Saks, A. (2022). Caring human resources management and employee engagement. *Human Resource Management Review, 32*(3), 100835.
Sanchez, R., & Hueros, A. (2010). Motivational factors that influence the acceptance of Moodle using TAM. *Computers in human behavior, 26*(6), 1632-1640.
Sarikaya, A., Correll, M., Bartram, L., Tory, M., & Fisher, D. (2018). What do we talk about when we talk about dashboards? *IEEE transactions on visualization and computer graphics, 25*(1), 682-692.
Sarmento, R., & Costa, V. (2019). Confirmatory factor analysis - a case study. *arXiv preprint*.
Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education, 128*, 13-35.
Scholtz, B., Mahmud, I., & Ramayah, T. (2016). Does usability matter? An analysis of the impact of usability on technology acceptance in ERP settings. *Interdisciplinary Journal of Information, Knowledge and Management, 11*(309-330). https://doi.org/https://doi.org/10.28945/3591
Schulze, A., Brand, F., Geppert, J., & Böl, G. (2023). Digital dashboards visualizing public health data: a systematic review. *Frontiers in public health, 11*, 999958.
Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. (2016). The elephant in the room: evaluating the predictive performance of PLS models. *Journal of Business Research, 69*(10), 4552-4564. https://doi.org/doi:10.1016/j.jbusres.2016.03.049
Stern, H. (2016). A test by any other name: P values, Bayes factors, and statistical inference. *Multivariate behavioral research, 51*(1), 23-29.

Surendran, P. (2012). Technology acceptance model: a survey of literature. *International journal of business and social research (IJBSR), 2*(4), 175-178.
Teo, T., & Zhou, M. (2014). Explaining the intention to use technology among university students: A structural equation modeling approach. *Journal of Computing in Higher Education, 26*(2), 124-142.
Tezel, A., Koskela, L., & Tzortzopoulos, P. (2016). Visual mangement in production management: a litterature synthesis. *Journal of manufacturing technology management, 27*(6), 766-799. https://doi.org/doi:10.1108/jmtm-08-2015-0071
Tufte, E. (2001). *The visual display of quantitative information.* Cheshire : CT. https://doi.org/Graphics Press
Tufte, E. (2013). *The visual display of quantitative information* ((2nd ed., 8th print) ed.). Graphics Press.
Turner, M., Kitchenham, B., Brereton, P., Charters, S., & Budgen, D. (2010). Does the technology acceptance model predict actual use? A systematic literature review. *Information and Software Technology, 52*(5), 463-479.
Vasnier, J.-M., Maranzana, N., Messaadia, N., & Aoussat, A. (2020). Preliminary design and evaluation of strategic dashboards through the technology acceptance model. *Proceedings of the design society: DESIGN conference. 1*, pp. 777-786. Cambridge University Press.
Vázquez-Ingelmo, A., Garcia-Penalvo, F., & Theron, R. (2019). Information dashboards and tailoring capabilities-a systematic literature review. *IEEE access, 7*, 109673-109688.
Velcu-Laitinen, O., & Yigitbasioglu, O. M. (2012). The use of dashboards in performance management: Evidence from sales managers. *The International journal of digital accounting research, 12*, 36-58. https://doi.org/doi:10.4192/1577-8517-v12_2
Venkatesh, V. (2022). Adoption and use of AI tools: a research agenda grounded in UTAUT. *Annals of Operations Research*, 1-12.
Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences, 39*(2), 273-315. https://doi.org/doi:10.1111/j.1540-5915.2008.00192.x
Venkatesh, V., & Davis, F. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision sciences, 27*(3), 451-481.
Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science, 2*, 186-204.
Venkatesh, V., Morris, M., Davis, G., & Davis, F. (2003). User acceptance of information technology: Toward a unified view. *MIS Quaterly, 27*(3), 425-478.
Wang, Q., Hou, H., & Li, Z. (2022). Participative leadership: a literature review and prospects for future research. *Frontiers in psychology, 13*, 924357.
Wong, K. (2013). Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. *Marketing bulletin, 24*(1), 1-32.
Yang, H., Yu, J., Zo, H., & Choi, M. (2016). User acceptance of wearable devices: An extended perspective of perceived value. *Telematics and Informatics, 33*(2), 256-269.
Yigitbasioglu, O., & Velcu, O. (2012). A review of dashboards in performance management: Implications for design and research. *International journal of accounting information, 13*(1), 41-59. https://doi.org/doi:10.1016/j.accinf.2011.08.002
Yousafzai, S., Foxall, G., & Pallister, J. (2007). Technology acceptance: A meta-analysis of the TAM: Part 1. *Journal of Modelling in Management, 2*(3), 251-280.
Zhuang, M., Concannon, D., & Manley, E. (2022). A framework for evaluating dashboards in healthcare. *IEEE transactions on visualization and computer graphics, 28*(4), 1715-1731.