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Sabina De Rosis, Veronica Spataro, Elisa Peruzzo, Hamish Laing, Milena Vainieri

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Determinants of user-reported data use for a data-driven public sector: Validating an adaptation of the UTAUT model with professionals and managers in healthcare

Déterminants de l'utilisation des données fournies par les utilisateurs dans un secteur public piloté par les données : Validation d'une adaptation du modèle UTAUT avec des professionnels et des gestionnaires de santé

Sabina DE ROSIS

Management and Healthcare Laboratory – Institute of Management & L'EMbeDS Department – Sant'Anna School of Advanced Studies – Italy

Veronica SPATARO

Management and Healthcare Laboratory – Institute of Management – Sant'Anna School of Advanced Studies – Italy

Elisa PERUZZO

Management and Healthcare Laboratory – Institute of Management – Sant'Anna School of Advanced Studies – Italy

Hamish LAING

Value-Based Health and Care Academy – Swansea University – Wales UK

Milena VAINIERI

Management and Healthcare Laboratory – Institute of Management – Sant'Anna School of Advanced Studies – Italy

ABSTRACT

Citizens'-reported data is crucial for improving service quality and innovation across various sectors, including healthcare. This construct-validating study focuses on understanding the determinants that prevent or encourage healthcare professionals and managers to use user-reported data. To explore these determinants, we adopted the *Unified Theory of Acceptance and Use of Technology* (UTAUT) model, which has been widely applied in various fields. This research is ongoing. Its first phase encompasses a qualitative study involving 13 semi-structured interviews with healthcare professionals and managers in Italy and Wales. The results from this phase will inform a subsequent quantitative survey involving a larger sample. Preliminary findings indicate that all the hypothesized UTAUT factors can influence the utilization of healthcare user-reported data. Participants confirmed the importance of performance expectancy, effort expectancy, social influence, facilitating conditions, habit, perceived security,

trust and anxiety as the main determinants. Future explorations will provide a comprehensive view of these factors in diverse user-reported data scenarios and digital platforms.

Key-words

User evaluation; User-reported data; Service management; Healthcare; Interviews

RÉSUMÉ

Les données fournies par les citoyens sont cruciales pour améliorer la qualité des services et l'innovation dans divers secteurs, y compris la santé. Cette étude se concentre sur la compréhension des déterminants qui empêchent ou encouragent les professionnels et les gestionnaires de la santé à utiliser les données rapportées par les utilisateurs. À cet effet, nous avons opté pour le modèle de la *Théorie unifiée de l'acceptation et de l'utilisation de la technologie* (Unified Theory of Acceptance and Use of Technology – UTAUT), largement appliqué dans plusieurs domaines. Cette recherche est en cours. Sa première phase comprend une étude qualitative impliquant 13 entretiens semi-structurés avec des professionnels et des gestionnaires de la santé en Italie et au Pays de Galles. Les résultats de cette phase permettront d'élaborer une enquête quantitative ultérieure impliquant un échantillon plus large. Les ré-

sultats préliminaires indiquent que tous les facteurs hypothésés par le modèle UTAUT influencent l'utilisation des données fournies par les utilisateurs du système de santé. Les participants ont confirmé l'importance de facteurs tels que l'attente de performance, de l'effort attendu, de l'influence sociale, des conditions facilitatrices, de l'habitude, de la sécurité perçue, de la confiance et de l'anxiété comme principaux déterminants. Les futures explorations fourniront une vue d'ensemble complète de ces facteurs dans les divers scénarii de données rapportés par les utilisateurs et des plateformes numériques.

Mots-clés

Évaluation par l'utilisateur ; Données fournies par l'utilisateur ; Gestion des services ; Santé ; Entretiens

1. INTRODUCTION

Data-driven decision-making is crucial for modernizing public administration.

Digital transformation enables, on the one hand, the production of great amount of data, and, on the other hand, an intensive use of data, presenting both opportunities and challenges for public organizations in their public value creation process. Public value has been defined under a multi-dimensional model (S. P. Osborne, 2018) where participation is articulated both as a means and an end to value creation process. In the realm of public service, value creation revolves around five key aspects including: (1) the influence of these services on users' satisfaction and overall well-being; (2) the outcomes produced by public services; (3) the impact of public services on the entire life

experience of citizens; (4) the capacity of public services to empower citizens for future challenges; and (5) the role of public services in generating value at a societal level (Osborne, 2020).

In an age where vast amounts of data are generated, ensuring that data are secure, reliable, and comprehensible for all users and participants in data-driven decision-making is crucial for increasing the public value. Digital technologies, such as artificial intelligence, can effectively utilize large datasets, manage information, and produce knowledge (Androniceanu, 2023; Valle-Cruz & García-Contreras, 2023). The digital technologies supporting data-driven decision-making can reduce bureaucracy and expense, while improving service quality, productivity, accessibility, and transparency (Androniceanu, 2023). Implementing these systems will significantly

enhance the way public organizations manage data throughout the value chain. Alexopoulos pointed broadly to a data-driven society as a benefit of applying digital tools such as artificial intelligence on data in the public sector (Alexopoulos *et al.*, 2019).

The Organisation for Economic Co-operation and Development (OECD) has defined the data-driven public sector, highlighting data as a valuable asset essential for evidence-based policy making, data-backed service design and delivery, organisational management, and innovation, and accountability, integrity, openness and fairness of decision-making as well (Van Ooijen *et al.*, 2019).

“A data-driven public sector recognises data as a strategic asset in policies and services design and delivery. It implies the development of sound data governance structures (including data strategies, institutional arrangements, rules) and related delivery mechanisms (data infrastructures, standards) to capitalise on the value of data to anticipate and respond to the needs of users, deliver better services and policies, and promote data integration, access, sharing and use across the public sector. A data-driven public sector also favours the use of innovative and alternative sources of data in the evaluation and monitoring of policies and services over time.”

(Ubaldi & Okubo, 2020)

The framework of van Ooijen, Welby, & Ubaldi (2019) illustrates that establishing a data-driven approach in the public sector is complex, non-linear and based on a recursive value chain. There is a loop between sharing and using/re-using data that, once initiated, can positively reinforce the first steps of the process. Data use and usability is, thus, a critical aspect in the instituting of a data-driven public sector.

Van Ooijen, Welby, & Ubaldi (2019) explored other several and significant challenges to the adoption of data-driven processes of decision-making. One of the primary challenges is obtaining useful data, which includes ensuring data availability, maintaining high standards of data quality, and ensuring the relevance of the data collected to the public sector’s needs. Data sharing, discoverability, and interoperability present

additional obstacles. Human and technical capacities must also be addressed by building a workforce with a diverse range of digital skills necessary to analyse and use data effectively. Legitimacy and public trust are also fundamental, so ensuring the ethical and accountable use of data and the need to act on data insights to drive improvements and, ultimately, value creation. Protecting the privacy of citizens and ensuring transparency in data use are also critical. Addressing these challenges is essential for unlocking the full potential of a data-driven public sector, enabling more informed decision-making, improving service delivery, and fostering innovation.

A case study by Choi and colleagues (2021) found that data-driven decision-making is influenced not only by technical factors such as data quality and coverage, compatibility and interoperability, availability of external data, information technologies and software, analytical techniques, privacy and confidentiality considerations, but also by organizational aspects such as cooperation among stakeholders, organizational culture, and public procurement policies (Choi *et al.*, 2021). The empirical study’s results suggested the need for comprehensive strategies to harness the full potential of data in improving decision-making, service delivery, and innovation in the public sector, with robust organizational and institutional support as key determinant for successful implementation of data-driven decision making.

More recently, Cantarelli and colleagues (2023) recognized three separate elements in comprehending how information is utilized in public organizations: the objective characteristics of information architecture; the subjective processes that involve cognitive biases (such as overestimating or underestimating the value of information) and decision noise (i.e., variability in decision-making); and the moderating influence of the different types of information users (Cantarelli *et al.*, 2023).

The common elements identified across these studies regarding the adoption and implementation of data-driven public sector decision-making can be summarized as follow: data quality and availability; technical and human capacities, including subjective elements in decision-making processes such as cognitive biases and decision noise; organizational and cultural factors; ethical and privacy considerations.

All studies point to the potential of data-driven decision-making to improve service delivery, foster innovation, and create value in the public sector, provided the above challenges are addressed effectively.

Thus, enabling data-driven activities requires investigating the conditions necessary for effective data use in the public sector, recognizing and addressing the challenges to unlocking data's full value.

Barcevičius *et al.* (2019) review of the literature identified numerous outputs of digital transformation in governments, such as new and renewed services, processes, skills, and products, by affecting internal processes and service delivery (Barcevičius *et al.*, 2019). Digital transformation in the context of public sector innovation can support efforts to enhance the quality of public services in a data-driven society by transforming service delivery. While data-driven approaches are often praised for their potential to improve efficiency, transparency, and responsiveness in public administration and management, critical perspectives have emerged regarding their broader social implications. Scholars have raised concerns about data justice, surveillance, and digital inequality, emphasizing the need to critically assess how data is collected, interpreted, and used. For instance, Brayne (2017) highlights how data-driven surveillance in public institutions can expand monitoring beyond known subjects, lower thresholds for inclusion, and integrate data from multiple sources – potentially reinforcing social inequalities and reducing transparency and accountability.

As reported by van Ooijen and colleagues (2019), the opportunities that can be derived from exploring the adoption of a data-driven culture within public organizations includes anticipatory approaches, implications on public service design and delivery, and impact on public performance monitoring and management. In particular, data-driven processes of decision making for service design and delivery implies leveraging data more effectively to comprehend issues and identify users, thereby responding more accurately to their needs. This involves using open communication methods and proactive data generation strategies, including collecting data from users. “*Engaging with citizens as co-value creators*” is reported among these strategies. Additionally, it highlights the move from top-down implementation assumptions to user-centered

design approaches, which consider contextual differences to tailor services and enhance flexibility.

To this regard, data-driven decision making can support also a truly “*customer-centric*” public service, by transforming the observation and listening of citizens and services’ users into data, knowledge and an opportunity of improvement and co-design. As written by Yves Caseau (2022) “*The revolution of the digital age of the 21st century is that customer orientation is more imperative – the era of abundance, usages rate of change, complexity of experiences, and shift of power towards communities – are easier, using digital tools and digital communities*” (Caseau, 2022). While the concept of customer orientation is well-established in the private sector, it differs significantly in public services. For publicly funded services, the term “*customers*” is often neither meaningful nor precise. Moore (2012) emphasized using the term “*citizen*” over “*client*” in the public sector, highlighting the blurred line between public service users and citizens (Moore, 2012). Citizens express fundamental needs, often constitutionally protected, which differ from private sector needs. Citizens support public services financially through taxes based on economic capacity, not individual needs. Thus, the real “*customers*” of public organizations are the collective citizens, who fund these services and act as collective overseers. On the other hand, there are the users of public services who can be extended to all individuals, regardless of their citizenship. Adopting user-centricity, despite inherent information and relational asymmetries, requires integrating user-reported data into measurements, evaluations, evidence to be uptake in data-driven decision-making processes. Public management approaches, like New Public Management, New Public Service, and Public Service Logic, emphasize citizen involvement in decision-making, with users as co-creators of value alongside public organizations. Moore (2012) discussed integrating the user satisfaction into public value measurements, suggesting public value is defined by the collective. The integration of this kind of data in the decision-making processes could create potential tensions to be addressed for understanding the contributions of decision-making also driven by user-reported data to the creation of individual and public value.

Understanding in the real-world the challenges to be addressed and how to co-create a data-driven process

of decision-making in the public sector cannot disregard the perspective of public servants who should use data and particularly data reported by public services' users. As highlighted by Baron and colleagues (2023), the shift from traditional public management to digital government overlooks the practicalities of administrative operations, which in turn is influenced by inner characteristics of the institutions, such as their complexity (Baron *et al.*, 2023; Dunleavy *et al.*, 2006). The co-creation with who should use the digital resources, in this case for supporting user-reported data use, is reported by Yves Caseau (2022) among the three capabilities of reference to derive more value from the digital transformation.

Despite the increasing amount of literature on data-driven decision-making, and more recently on big data, there are still few empirical studies examining processes and strategies that government agencies use to implement this approach with a clear request for studies exploring the fundamental conditions necessary for advancing the research on data-driven decision making (Choi *et al.*, 2021).

To the best of our knowledge, there is also a gap in literature about the conditions that support user-reported data uptake in a data-driven decision-making process.

Given these premises, this construct-validating research is aimed at adapting and proposing to academics and practitioners a tool for understanding the determinants that prevent or encourage public employees, professionals and managers to use data reported by users in their decision-making processes. The application of the study is the public healthcare sector in two countries, namely Italy and Wales.

This study represents the initial phase of a broader research project focused on identifying the key factors that support or limit the use of user-reported data within healthcare organizations. This is an analytic generative study since the findings are generalized to theoretical propositions by extending the constructs behind the UTAUT model. The findings of this phase, aimed to design and present a tool to explore the elements influencing patient-reported data uptake, will be used in the next phases of the study for collecting cross-national data to determine how specific UTAUT constructs predict data use in public healthcare organizations.

2. WHY THE PUBLIC HEALTHCARE SERVICES?

Studying the public healthcare sector is crucial due to its significant role in public service delivery, which is extensively considered in the literature alongside public safety and security (Codagnone *et al.*, 2020).

The public healthcare sector, particularly systems that ensure universal coverage under the Beveridge model, has unique characteristics in terms of stakeholder composition and relationships. Key stakeholders include citizens (and patients as a subgroup), national and regional policymakers, healthcare managers, and professionals (De Rosis *et al.*, 2019, 2020; Nuti *et al.*, 2016). Differently from healthcare mainly funded by insurance under the Bismarck model (such as Netherlands, Germany etc.), in the Beveridge models, citizens, through their taxes, fund the healthcare system and elect policymakers who set strategies and choose management. Policymakers shape the healthcare system's policies and goals, while managers ensure that healthcare professionals can perform their duties effectively, managing the organization's performance and financial sustainability. Healthcare professionals, such as doctors and nurses, deliver services in various settings, significantly influencing patient care quality and costs.

The literature categorizes citizens into consumers, clients, users, and patients, each with different needs and interactions with the healthcare system (Herxheimer & Goodare, 1999). Consumers purchase health-related goods, clients use professional healthcare services, users have utilized or might utilize any healthcare service, and patients seek treatment due to illness. Caregivers, who support patients, also play a crucial role.

Healthcare services are highly relational and emotionally intensive, impacting patient experiences and satisfaction (Berry, 2019; Berry *et al.*, 2015; McColl-Kennedy *et al.*, 2017). The interactions between healthcare providers and patients are vital for positive service experiences, a good perception of service quality, and for reinforcing the trust in the service providers and the whole system. The asymmetry of information between patients and providers means patients rely heavily on the professionals' expertise, which can lead to anxiety and uncertainty.

Involving all stakeholders is essential to meet user needs and ensure the system's responsiveness. Patient engagement is increasingly recognized as critical for effective healthcare delivery. It is not only about sharing decision-making at the point of contact and participating actively in their care, leading to a shift from a paternalistic approach to a collaborative partnership. Patients are now seen as co-producers in healthcare, contributing valuable knowledge. This collaborative model emphasizes mutual value creation between patients and healthcare providers, enhancing the overall effectiveness and satisfaction within the healthcare system, and supporting a user-centric approach to the service delivery (Batalden *et al.*, 2016; Godlee, 2017; Richards *et al.*, 2013; Voorberg *et al.*, 2014).

The person-centered approach in healthcare (Håkansson Eklund *et al.*, 2019) places current or potential users, whether they are clients, consumers, patients, caregivers, at the centre of individual decision-making processes at the micro level, as well as the assessment of service quality at the public organization and public system levels of the healthcare sector. According to Tseng and Hicks (2016), experience measures reported by the healthcare service users would facilitate aligning the person-centred approach with value-based care, because the use of these data could nourish the processes of decision-making at all the levels of the healthcare sector, from the micro level of the encounter between the patient and the doctor, to the macro level of the policy making, with the aim of creating value both at the individual and collective levels (Tseng & Hicks, 2016). Therefore, studying the public healthcare sector provides valuable insights into how digital innovations can revolutionize service delivery and encourage the transition towards more user-centric approaches by supporting a user-reported data-driven decision-making.

In addition, the healthcare sector's widespread adoption of digital innovations has led to a shift from traditional face-to-face care to digitalized delivery of services. These advancements also enabled continuous and real-time information collection about patients and their experience with services (De Rosis *et al.*, 2020). Digital technologies can, thus, empower citizens to report about public services' quality, enhancing their engagement (Codagnone *et al.*, 2020). Authors exploring opportunities to achieve fairness and equity in data-driven public administrations

argue that data can empower marginalized groups, like patients, by engaging them as collaborators in the process (Ruijter *et al.*, 2023).

Understanding the impact of digital transformation for a data-driven public healthcare is essential because it highlights the sector's ability to adapt to and integrate new technologies for better service design and delivery, and for monitoring and improving the performance as well.

2.1. The challenges to user-reported data-driven public healthcare

The literature highlighted the importance of user-reported data for improving service quality as well as for service innovation, in different sectors, including healthcare. Indeed, user-reported data is essential for improving the quality of services, detecting service gaps, and raising service standards; it helps organizations understand the needs, preferences, and expectations of their users, so they can better handle user complaints and other issues and make the required adjustments (Murante *et al.*, 2014; Pai & Chary, 2013; Parasuraman *et al.*, 1988, 1994). Moreover, user opinions can be a great source of inspiration and knowledge for service innovation. Organizations can use consumer-reported data to discover new service opportunities, identify emerging trends, and create cutting-edge service offers (Berry, 2019; Osborne *et al.*, 2016; Prahalad & Ramaswamy, 2004b, 2004a). Managing user-reported data can be complex and challenging for organizations (Da Silva, 2021). For instance, even though many departments and functions have systems in place to track user-reported data, few organizations have an integrated, corporate-wide perspective on user experience (Da Silva, 2021). In this sense, factors such as integrity, reliability, and robustness of the data collection and use process, but also time and effort, obstacles and bureaucracy need to be taken into consideration (Da Silva, 2021). Moreover, after data collection, companies still need to produce relevant user insights or knowledge about users that create value for the organization. In this sense, data analysis is important, as is using the results for decision-making (Holmlund *et al.*, 2020).

In healthcare, user evaluation can be collected via outcomes and experience measures (in general referred

to as patient-reported measures) (De Rosis *et al.*, 2019, 2022). However, collecting patient opinions through surveys is not enough to change the behaviour of public servants. Data should be used by managers and professionals for improving the quality of services, their responsiveness, their potential innovation and re-design (Coulter *et al.*, 2014). More precisely, the experiences of application of patient-reported measures can be categorized along two key dimensions: the level of data aggregation and the use in the doctor-patient relationship (Brundage *et al.*, 2013; Snyder & Aaronson, 2009). Individual-level aggregated patient-reported data can be used as screening tools to identify specific issues (e.g., anxiety, depression, physical and social functioning). In this context, they serve to monitor the impact of a particular treatment on an individual patient, promoting a patient-centred care approach that focuses on the patient's perspective. In this case of group/population-level aggregation, data are used to support decision-making regarding different interventions or treatments and whether patient needs have been met by the healthcare system. The focus is on the effectiveness and overall impact of care at a population level. When data are used as decision-support tools in the doctor-patient relationship, they can facilitate structured exchanges of information on often overlooked topics, offering a common language among professionals from various disciplines, which is particularly useful in managing complex patients, such as elderly individuals with chronic conditions. When data are not used within the patient-doctor relationship, they can be employed as quality-of-care assessment tools. These tools enable the evaluation of the quality of care (particularly in terms of effectiveness) and allow for comparisons between providers (e.g., hospitals), with the goal of improving the quality of healthcare on a larger scale. To bring about a change, it is important to incorporate the patient experience and outcome improvement goals into the planning, feedback, and assessment procedures (Ferreira & Otley, 2009; Murante *et al.*, 2014). Yet, patient-reported outcomes are seldom used to estimate the value of different interventions and whether patient needs have been met by healthcare system in real world evidence (Manetti *et al.*, 2024; Nguyen *et al.*, 2021).

Barriers have been highlighted in the literature about the use of healthcare user-reported data as a routine management tool (Coulter *et al.*, 2014; Lungu *et al.*,

2020; Porter *et al.*, 2016). One key factor is data sharing and dissemination, also using digital infrastructure to turn data into actionable insights for decision-making (Flott *et al.*, 2017; Gleeson *et al.*, 2016). Indeed, user-reported data increasingly are provided to healthcare professionals and managers with different types of technologies (Johanssen *et al.*, 2019). The use of technological tools can influence the frequency with which professionals acquire user-reported data. In this sense, reducing manual steps in favour of (semi)automated processes may encourage approaches that allow continuous and systematic user-reported data, rather than periodic contexts (De Rosis *et al.*, 2020; Johanssen *et al.*, 2019).

In this sense, the UTAUT (*Unified Theory of Acceptance and Use of Technology*) model (Venkatesh *et al.*, 2003) can be a useful lens to investigate the topic of the use of patient-reported data in healthcare organizations. This model is tested in the healthcare sector for verifying whether its determinants are valid also when applied at the use of patient-reported data by managers and healthcare professionals in their decision-making processes. In this study, we adopted a qualitative approach to validate the UTAUT model within the healthcare sector for twofold reasons. The UTAUT model, while widely used across various fields, was not originally designed nor for healthcare nor for data as essential component of the digital sphere. It has been applied to the evaluation of determinants of mobile applications, wearable technologies, websites and digital dashboards. Although there are studies applying UTAUT to healthcare technologies, there remains a lack of evidence regarding how users interpret the model's items or whether they feel certain key factors are missing when handling information, figures, statistics and so on. This study addresses this gap by using qualitative data to explore the model's relevance and validity in using data within the healthcare context. Furthermore, while existing research has investigated or validated UTAUT in healthcare through quantitative methods, our study offers a novel contribution by employing a qualitative approach, which allows for a deeper understanding of the public servants' perspectives.

3. WHY ITALY AND WALES?

The study was conducted in different regional healthcare systems in two countries, namely Italy and Wales, since they have a similar organizational structure and have established experience of collection of patient-reported data.

Both countries have healthcare systems that are primarily public and based on principles of universal access to healthcare under the Beveridge model, funded by the citizens' taxes and with devolution granting autonomy in health management at the regional level (Bevan *et al.*, 2014; Donatini, 2020; NHS Wales, 2020; OECD, 2019).

In National Health Service (NHS) Wales clinical services increasingly collect PROMs (*Patient-Reported Outcome Measures*) as part of routine care and use them to inform shared-decision making and transform the way healthcare is delivered to achieve better outcomes that matter to patients (EIT Health, 2020; Withers *et al.*, 2021).

In 2018, the Welsh Government has explicitly emphasized the importance of involving patients in decisions regarding their care – (NHS Wales 2018). It has established that the planning and delivery of services will be grounded in prudent healthcare principles and value-based healthcare. Implementing value-based healthcare represents a significant cultural and transformational shift in Wales, emerging from grassroots efforts as a means to realize the goals of Prudent Healthcare. The NHS Wales is committed to supporting the implementation and development of outcome measurements and cost analysis through a collaborative data-sharing approach, to enhance the quality of healthcare services and increase value for patients. This entails measuring healthcare costs at the system level and making this information accessible to clinical teams, empowering them to manage resources effectively and promote high-value care for the populations they serve. Healthcare organizations in Wales are dedicated to advancing value-based healthcare initiatives. This commitment includes improving the collection and reporting of holistic outcome data across various medical conditions and analyzing unwarranted variations in services and

outcomes. These PROMs collection initiatives can support the identification of areas of both underuse and overuse within the healthcare system. PROMs may provide useful communication between a person and their healthcare team to support direct care, or enable a person to track their own progress or recovery. They should therefore not just be viewed as an end point, but they can also be a milestone or status at a point in time for an individual to report how they are faring – in areas of their life that matter to them, and in a structured way. Aggregated PROMs can provide a useful needs assessment, helpful in determining local or national service development. Different condition pathways have been nationally agreed by clinical reference groups and all of these pathways are currently available on a national platform. For healthcare professionals, PROMs can play a crucial role in optimizing outcomes at multiple levels. For individual patients, PROMs help the clinical team focus on what truly matters to them. By analyzing aggregated PROMs data, patients can make informed decisions about their care, drawing from the experiences of others with similar conditions. At the cohort level, PROMs provide valuable data that can inform improvements to patient pathways, evaluate the outcomes of specific treatments, and guide the appropriate selection of patients for those treatments.

On a health board and population level, PROMs data can lead to more efficient and effective care, while also reducing expenditure on low-value interventions. This opens up opportunities for reinvestment in treatments that deliver real value in healthcare. In Wales, the collection of generic PREMs is guided by a national approach from the Welsh Government, with an updated questionnaire recently implemented. A digital platform has been rolled out nationally to collect Patient Reported Experience Measures (PREMs). The national clinical framework encourages the use of PREMs by specialties, with many now implementing condition-specific PREMs locally. Efforts are also underway to establish data and interoperability standards for PREMs, similar to PROMs.

The Italian National Health Service has always promoted the collection and use of the patient's voice, facilitating the participation of healthcare services' users in the evaluation of services. The Italian reform introduced by the Legislative Decree No. 502/1992 requires that healthcare organizations and regional

systems to establish “*monitoring and control systems [...] on the quality of care and the appropriateness of the services provided*”, including “*the satisfaction of service users*” (art. 8 octies). This has supported the spread of several experiences of PREMs collection. Given the fragmented situation due to the decentralization of organizational power to the Italian Regions, the Italian experiences have been mainly one-shot initiatives in the form of patient satisfaction surveys, managed at the single hospital level, or at the regional healthcare system level, such as in the regions of Tuscany, Lombardy, Emilia-Romagna. The only systematic surveys at the national level are targeted at representative samples of the general population by the national statistical institution ISTAT. Approximately every five years, a sample survey on “*Health Conditions and Use of Healthcare Services*” is administered. Apart from some regional initiatives (De Rosis *et al.*, 2020), briefly described below, there are no systematic and continuous national patient surveys across Italian regions. Recently, the 2019-2021 Italian Health Pact highlighted the importance of customer experience and citizen participation in the evaluation of services. Specifically, in Sheet 14 on “*Tools for Citizen Participation and Personalized Access to Healthcare Services*”, it underscores the relevance of “*promoting and implementing enabling tools that improve interactions and the customer experience*” also through “*the adoption of shared rules, standards, and codes for the interoperability and integration of ecosystems*”.

The above-mentioned examples of routine collection of PREMs (De Rosis *et al.*, 2020) and PROMs (De Rosis *et al.*, 2021; Ferrè *et al.*, 2021; Lungu *et al.*, 2020; Pennucci *et al.*, 2020) have been piloted in Tuscany region and then joined by other regional healthcare systems or organization, with the scientific support of the MeS Laboratory. The routinely collection of PREMs and PROMs has formally started in the period 2017-2018. The methodology employed the systematic and continuous collection and reporting of data, so building an intra and inter-regional Observatory, allowing the use of the same tools of patient-reported data collection and the potential of benchmarking of data across Italian regional healthcare systems joining the Observatory (De Rosis *et al.*, 2020). The PREMs and PROMs Observatories have been joined by various Italian regions (De Rosis *et al.*, 2020). The patient-reported data have become

important tools of accreditation and measures of hospital performance, and have been progressively integrated into the Performance Evaluation System of the MeS Laboratory (De Rosis *et al.*, 2022; Gilmore *et al.*, 2019). In light of this, in 2019, as part of its participation in the experimental phase of the OECD PaRIS (*Patient-Reported Indicator Survey*) project on primary care and chronic conditions, the Italian Ministry of Health planned and subsequently initiated a national pilot aimed at establishing an Observatory on experience and outcome measures reported by chronic patients. This Observatory would systematically and continuously capture the voice of patients at the national level, potentially and eventually building a patient-reported information flow that integrates data from the Ministry’s administrative records (Vainieri *et al.*, 2022).

In both countries, the collection and use of patient-reported data are supported by digital platforms. These latter are aimed at making possible access and review of patient-reported data for healthcare managers and professionals. In Wales, patient-reported measures are accessible in dashboards at both in aggregated form and at individual level with appropriate access-control. In particular, PROMs are accessible to professionals at the patient level for individual care and decision-making. Patient-reported data are integrated within Electronic Health Records (EHR) allowing for more systematic data collection and use. On the contrary, in the Italian system, web-based platforms of the above-mentioned Observatories were developed exclusively for making aggregated patient-reported data accessible to healthcare providers and managers. This kind of systems are mainly aimed at enhancing managerial decision-making and promoting quality improvement actions (De Rosis *et al.*, 2020). The aggregated data from the Italian Observatories are also accessible using web services, thus allowing healthcare organizations to build their own dashboard or to integrate data with other business intelligence systems of data reporting, analysis and spreading.

Considering these setting, this study uniquely validated the UTAUT construct in two different countries, Italy and Wales.

4. METHOD

The study employs a qualitative method, leveraging the UTAUT model to assess the appropriateness and relevance of adopting its traditional determinants as valid conditions under which healthcare professionals and managers utilize user-reported data in their decision-making processes. This investigation focuses on both facilitators and obstacles to the adoption of such data in a context of data-driven public healthcare systems.

Interviews were employed in a process of face validity of constructs, to assess whether the UTAUT model appears to measure what it is intended to measure. This type of validation is concerned with the appropriateness, relevance, and clarity of the items from the perspective of those who are taking or reviewing the questionnaire, such as subject matter experts or potential respondents.

In line with Eisenhardt (1989) notion of analytic generalization, the method we adopted can provide findings to extend, enrich, and question existing theoretical understandings of how patient-reported data-driven mechanisms shape managerial decision-making in public healthcare.

4.1. The UTAUT model

The UTAUT model assesses the likelihood of success for the introduction of new technology (Venkatesh *et al.*, 2003). Its development has provided both a research and managerial tool to understand the drivers of technology acceptance in order to proactively design interventions (including for instance training and communication) targeted at populations of users that may be less inclined to adopt and use new systems. The main components of the UTAUT model are derived from previous theoretical technology acceptance models (e.g., Technology Acceptance Model, Theory of Diffusion, Theory of Reasoned Action and Theory of Planned Behaviour). These include performance expectancy, effort expectancy, social influence and facilitating condition which are considered the main influencing factors of intention to use a particular technology. In addition to the three direct determinants of intention to use (performance expectancy, effort expectancy, and social influence – Venkatesh *et al.*,

2003) posit two direct determinants of usage behaviour (intention and facilitating conditions).

Venkatesh and colleagues (2011) developed a first extension of the UTAUT models, to integrate expectation-confirmation theory for information systems' usage. Subsequently, the UTAUT2 model incorporates three new constructs; hedonic motivation, price value, and habit into the original UTAUT (Venkatesh *et al.*, 2012).

The model and its extensions have been used to study the attitude of individuals with technologies, some specific services, or ways of using services. Since being introduced, the UTAUT model has been tested extensively in various fields for analysing users' acceptance of technology, including in healthcare. For instance, drawing from the UTAUT model, Kohnke and colleagues (2014) investigated the predictors of the intention to use Telehealth equipment by patients, clinicians, and agency personnel (Kohnke *et al.*, 2014). Cimperman *et al.* (2016) applied the UTAUT model to test the acceptance behaviour of telehealth technology and services, showing that behavioural intention can be studied also at a conceptual level rather than in relation to a specific technology. Roudi *et al.* (2022) used both the UTAUT and the Technology Acceptance Model (TAM) models to predict the acceptance behaviour of remote care technologies by health professionals (Roudi *et al.*, 2022). Wang and colleagues (2020) used the UTAUT and task-technology fit models to understand how consumers accept healthcare wearable devices (Wang *et al.*, 2020). Moreover, specific studies focused on the mobile payment context, introducing the concepts of technology reliability and privacy issues (Lee *et al.*, 2019; Slade *et al.*, 2013).

To investigate the factors influencing the adoption of data use by public servants, we drew upon established technology acceptance models, as mentioned above. While these models have been widely applied to study user acceptance of digital technologies, also in the public sector and in the healthcare context, some authors stated they may not fully capture the specific dynamics of the public sector (Salama & Farag, 2024). Other additional factors often play a more central role in shaping attitudes toward digital tools and data use in public contexts. A recent systematic literature review on the adoption of e-government among public sector

employees identified three main themes through thematic analysis: human factors, technical factors, and organizational factors (Abdul Wahi & Berényi, 2023). Our study incorporated all three dimensions in the selection of factors.

In fact, we did not rely solely on the core components of the original UTAUT model (Venkatesh *et al.*, 2003). Instead, we expanded our framework by incorporating and adapting additional constructs found in the literature to better suit the public sector context and to guide our interview protocol. The first four factors – performance expectancy, effort expectancy, social influence, and facilitating conditions – were adapted from the original UTAUT model of Venkatesh *et al.* (2003; 2011; 2012), Cimperman *et al.* (2016), and Lee *et al.* (2019). The construct habit was adapted from Venkatesh *et al.* (2012); trust from Venkatesh *et al.* (2011); and perceived security and anxiety from Cimperman *et al.* (2016). This expanded set of factors was used to inform both the structure and content of our interviews, allowing for a more nuanced exploration of public servants' attitudes and behaviours regarding data use. The factors used in this study are explained in the following lines.

4.1.1. Performance expectancy

One of the core components of the UTAUT model is performance expectancy, which is defined as “*the degree to which an individual believes that using a system will help him or her to attain gains in job performance*” (Venkatesh *et al.*, 2003, p.447). In the context of this study, performance expectancy refers to how much healthcare professionals and managers believe that using patient feedback will help them improve how they perform their job duties.

4.1.2. Effort expectancy

Effort expectancy in UTAUT is described as “*the degree of ease associated with the use of a system*” (Venkatesh *et al.*, 2003, p.450). In this study, it is understood as how easy or straightforward it is for healthcare professionals and managers to use patient feedback in their everyday work. The focus is on the ease of using the data itself, rather than on the tools used to collect it.

4.1.3. Social influence

Social influence refers to “*the degree to which an individual perceives that important others believe he or she should use the new system*” (Venkatesh *et al.*, 2003, p.451). For example, a recent study highlighted the crucial role of clear regulations and strong top management support in the adoption of e-government (Alfiani *et al.*, 2024). In this study, it reflects how much professionals and managers feel influenced by people they consider important – such as colleagues, supervisors, or policymakers – who believe that patient-reported measures should be used.

4.1.4. Facilitating conditions

Facilitating conditions are defined as “*the degree to which an individual believes that an organisational and technical infrastructure exists to support the use of the system*” (Venkatesh *et al.*, 2003, p.450). In this study, they are understood as the organisational resources and support (e.g., training, tools, time) that professionals feel are in place to enable them to use patient feedback effectively within healthcare organisations.

4.1.5. Habit

Habit was added to the UTAUT model as a factor influencing continued use of technology (Venkatesh *et al.*, 2012). It reflects how much someone feels that a certain behaviour has become automatic. Limayem *et al.* (2007) stressed that repeated actions can become habits over time and should not be overlooked when studying system use. They define habit in information system use as the extent to which people act automatically due to past learning. Their model shows that continued use of a system depends not only on intention but also on habit. In this study, habit refers to how much the use of patient feedback has become a standard or expected part of organisational routines, and how likely professionals and managers are to use it as part of their daily work.

4.1.6. Perceived security

Lee *et al.* (2019), drawing on Yang *et al.* (2015), define

privacy risk as a person's perception that their private information could be exposed. These concerns can reduce the willingness to use digital systems, such as mobile payments. Cimperman *et al.* (2016) describe perceived security as including aspects like how reliable a technology is, and how well it protects personal data. In their work, this is particularly important for older adults deciding whether to accept telehealth services. Based on this literature, this study defines perceived security as including both the safety of the data (data security) and whether its use complies with privacy laws, especially regarding sensitive patient information. This is particularly relevant in the context of the EU's General Data Protection Regulation (GDPR) and the Italian Data Protection Authority's guidelines. Healthcare organisations, in particular, must be very careful with personal data, especially health information that can identify a person (De Rosis *et al.* 2022; Gostin *et al.*, 2018; McGraw & Mandl, 2021; Tucker *et al.*, 2016).

4.1.7. Trust

According to Venkatesh *et al.* (2011), trust means believing that another party will act cooperatively and not take advantage of one's vulnerabilities. For example, when people shop online, they trust that companies will handle their private information (like credit card details) responsibly. In this study, trust is defined as how much professionals and managers believe in the usefulness of patient-reported measures in their work, and in the value of data to support high-quality service delivery and sound management decisions.

4.1.8. Anxiety

Anxiety refers to negative attitude towards technology (Kohnke *et al.*, 2014). In the study context, it is considered the extent to which healthcare professionals and managers feel confident in utilizing patient feedback. The integration of this factor becomes particularly relevant and interesting since it may reflect a deeper unease about how data is used, the potential for misuse, and the professionals' own confidence in engaging with data and digital feedback systems as well (Brayne, 2017) – especially in sensitive fields like healthcare.

4.2. Data Collection

13 semi-structured interviews were conducted with healthcare professionals and managers from Italy and Wales.

We adopted a convenience sampling strategy. However, participants were not chosen simply for ease of access; rather, they were selected based on their relevance to the research topic and the study's objectives (Denscombe, 2017). Specifically, they were recognised within the two public healthcare systems encompassed by this study as either leading experts or professionals with extensive experience in the patient-reported data.

A semi-structured approach followed a clear set of topics (Supplementary Materials), whilst allowing flexibility in the order and depth of discussion. We used open-ended questions, encouraging interviewees to elaborate and explore issues more freely on constructs, items and wording. The interviews explored their perspectives on the determinants of the use of the healthcare service user-reported data, encompassing the adoption of the UTAUT model and its extensions to adapt it to the context of the use of patient-reported measures by healthcare professionals and managers. The interviewees were asked to answer i) general questions on the relevance of the different factors and the completeness of the hypothesized model, ii) specific questions on the items measuring each factor, for evaluating clarity and coverage, as well as length and format of questions, and iii) any examples relating to their practice. Interviewees were asked to provide detailed feedback on each item, identifying any questions that seem irrelevant, confusing, or poorly worded. They might suggest rewording, removing, or adding questions to improve the questionnaire's validity. The interview scheme was developed and discussed by three of the co-authors to ensure consistency of the questions across both countries and alignment with the study's research objectives. Each interview was carried out by a minimum of two members of the research team, all of whom are also co-authors of this study. One researcher led the interview while the other took notes. The interviews typically lasted between 45 and 60 minutes. A total of 13 interviews were conducted, at which point data saturation was reached – meaning that further interviews were unlikely to yield new information

or significantly alter the existing codebook (Guest *et al.*, 2006).

The decision to engage a small number of participants aligns with established qualitative research practices. As noted in the literature, the number of interviews in qualitative studies varies depending on the study’s goals – for instance, around 12 in the study by Guest *et al.* (2006), between 5 and 25 according to Creswell &

Poth (2018), and from 10 to 15 in Patton’s (2015) guidelines. Since our research addresses a well-defined subject and data saturation was reached, we considered 13 participants to be adequate for generating valuable insights while ensuring manageable data collection and analysis.

The characteristics of the participants are reported in Table 1.

| Variables | | Categories | Values (n) | Values (%) |
|-------------------------------------|---------------------------------------|--------------------------------------|------------|------------|
| Country | | Italy | 6 | 46% |
| | | Wales | 7 | 54% |
| Sex | | Female | 9 | 69% |
| | | Male | 4 | 31% |
| Role | | Manager with clinical background | 5 | 38% |
| | | Manager with non-clinical background | 6 | 46% |
| | | Clinician | 2 | 15% |
| Familiarity with user-reported data | | Yes, partially | 2 | 15% |
| | | Yes, totally | 11 | 85% |
| Seniority | Years working in the current position | Less than 3 years | 4 | 31% |
| | | 3-5 | 3 | 23% |
| | | 6-10 | 2 | 15% |
| | | More than 10 | 4 | 31% |
| | Years working in healthcare | Less than 5 years | 2 | 15% |
| | | 10-20 | 2 | 15% |
| | | 20-30 | 6 | 46% |
| | | More than 30 | 3 | 23% |
| Current use of user-reported data | | Yes | 11 | 85% |
| | | No | 2 | 15% |

Table 1 – Characteristics of participants in the interviews

Source: Authors

5. RESULTS

First, the findings of this study confirm the validity of the model in the context of the public healthcare sector. The participants validated the importance of the proposed factors as the main determinants of the use of healthcare user-reported data, as well as the model's completeness, without the need to add new factors to cover missed areas. No relevant differences emerged in the perception of factors among the various informants, based on the characteristics mentioned above.

The questionnaire was revised to address feedback about some of the wording used. This involved rewriting questions for clarity and removing items that did not seem relevant.

Specifically, the *“performance expectancy”* factor remained consistent with the proposed scale, adapted on the basis of the previous studies applying the UTAUT model, retaining its five statements.

In contrast, the *“effort expectancy”* factor was reduced from four to two statements. This decision was based on feedback received from interviewees who felt that *“certain statements are redundant”*.

In the *“social influence”* factor, the references to the *“social circle”* and *“People who are important to me”* in the UTAUT model have been deleted (*“The statement is too ambiguous and doesn't fit well in the professional context”*, *“The people that are most important to me are outside of the work context”*, *“social circle mainly refers to my personal-family sphere”*). Participants underlined the importance of maintaining the organizational level, peers, institutional and external bodies.

The *“facilitating conditions”* factor was expanded from six to seven statements. The concept of *“resources”* was declined in material resources, human resources and time (*“Resources are very generic”*). Additionally, *“guidance”* and *“specialized instructions”* were incorporated into a single statement (*“These two statements are overlapping”*), which also included the *“training”* (*“there is an issue with people feeling confident using data, which means that there is a gap in training, knowledge and skills”*,

“Often people don't get any training to use these data”, “training on how to use the software”). The *“habit”* factor was reduced from four to three statements because they are considered as being *“redundant”* by the participants.

Concerning *“perceived security”*, professionals underlined the importance to collect and report patient data in a safe way. However, they also suggested to add the focus on data sharing (*“Is sharing safe?”*, *“Collection, reporting and sharing. How it was collected and how it was reported is known and where they are shared is not known. With whom? On which sites/platforms?”*).

The *“trust”* factor remained consistent with the proposed scale, adapted on the basis of the previous studies applying the UTAUT model, retaining its four statements. Finally, the *“anxiety”* factor was better adapted to the study context, following the suggestions of the interviewees.

After revisions, the questionnaire underwent a final review to ensure that it met the expectations for face validity. At this stage, the questionnaire appears to be a concrete, effective and accurate tool for investigating the factors affecting the uptake of user-reported data in the decision-making processes of public servants, both to experts and to typical respondents (Appendix).

Second, the interviews allowed in-depth discussion of each factor of the model, to better understand its meaning and the perception of its relevance in the informants' perspectives in two different European countries.

5.1. Is performance expectancy a determinant factor for the use of healthcare user-reported data?

During the interviews, it emerged that performance expectancy plays a pivotal role in determining the utilization of healthcare user-reported data. Participants recognized that performance expectancy serves as a motivating factor, as it directly impacts their decision to engage with user-reported data. Healthcare user-reported data is useful *“to look back at things we have done and look at how we can change things*

for the future”, “allows you to [...] do the things that are effective”, “allows you to review and improve productivity based on the experience”, “to improve the service in line with what the service user wants”, “to be client-centred”. Healthcare user-reported data were reported by the informants to be useful when consulting with patients; to identify areas where professionals need to focus or the area where patients are most concerned; to ask more direct questions to patients; and to better understand the current medical status of the patient (so both to inform treatment and service delivery). In addition, the informants also recognized the valuable role of user-reported data at the organizational (“meso”) level (e.g., for service delivery and service design) and the system (“macro”) level (e.g., for monitoring, evaluating and benchmarking the performance results in the user perspective).

5.2. Is effort expectancy a determinant factor for the use of healthcare user-reported data?

Informants emphasised the importance of acknowledging the work required for adopting and utilising user-reported input. They stressed the importance of aligning effort expectations with the goals and objectives of healthcare organizations, considering current constraints and challenges. This alignment not only encourages healthcare providers to actively seek and use patients-reported data, but also ensures that the data loop remains a valuable tool for enhancing the overall quality of healthcare services (“Having this information available allows me to have a clearer idea of the patient’s needs”). This factor appeared strictly linked with the technical and digital tools used to collect, access and analyse data. Two aspects emerged as important about this factor: the ease of use of the tool, and the ease of use of the information provided (“Can you use the information you get from them?”).

5.3. Is social influence a determinant factor for the use of healthcare user-reported data?

The interviews revealed that social influence is a key factor in the use of healthcare user-reported data. Two major influences need to be taken into consideration in their point of view: the organization and the

peers. The organizational level refers mainly to managerial mechanisms that are put in place for enhancing the uptake of data in the decision-making processes, such as managerial mechanisms of control (i.e., monitored key performance indicators). Peer-pressure is another factor that was emphasized by informants, referring to the importance of sharing good practices of data interpretation and use among public servants (i.e., into communities of practice), but also mentioning the importance of the reputational levers and the consequent “me too” effect. Furthermore, institutional (i.e., “national, regional and local healthcare systems”) and external bodies (e.g., “university”) play a crucial role in stimulating the use of patient-reported data (“We feel part of a network”). This demonstrates the importance of considering the close collaborations of healthcare organizations with professional bodies operating at different levels of the healthcare system, or third-party bodies that collaborate and can support organizations in different activities.

Additionally, “there is a difference between supporting and valuing the use of them”, meaning that while someone may verbally support or express positive intentions towards using patient-reported data by professionals, truly valuing them requires concrete actions. This includes implementing policies, providing resources, and offering incentives that actively promote and integrate their use within the healthcare system. Indeed, support can be seen as rhetorical, but value is demonstrated through practical commitment and real-world application. So, “it is important to consider also this last aspect” that refers to acknowledging the efforts of user-reported data uptake into the decisions, with tangible (i.e., goals linked to the additional payment) or intangible benefits (i.e., public recognition during events).

5.4. Are there any facilitating conditions for the use of healthcare user-reported data?

The insights gleaned from these interviews shed light on the significance of having some facilitating conditions within healthcare organizations, and how they influence professionals’ and managers’ willingness to integrate user-reported data into their practice (“Without facilitating conditions nothing can be done”). More specifically, participants prefer

to distinguish between material resources (e.g., the “infrastructures to use them”, “practical things like computers, pen and paper stamps and/or digital solutions”), human resources (e.g., a team of people working on collecting and consulting data), and knowledge, which can relate to statistical knowledge (e.g., how to interpret raw data, or how to present results). Informants reported that decision-makers can strongly benefit of data controllers, processors and analysts to effectively use these data. Another key aspect of this factor focuses instead on the ability of patient data to be complementary with other measures and systems used by the organization. In this sense, for healthcare professionals, the possibility of using this information collected together with others, to have a more complete vision, appears to be an aspect to take into account.

Moreover, the participants highlighted that time is considered a big barrier, and it needs to be taken into consideration together with the other types of resources (“for example, I’ve got the equipment, I haven’t got the time, or I’ve got the equipment and the time, or I haven’t got the equipment, and I haven’t got the time”). The results also confirmed the importance of having some support (a specific person or group available for assistance) as well as guidance, specialized instructions and/or training, since new skills and competences are to be established and nourished for an effective data-driven decision-making.

5.5. Is habit a determinant factor for the use of healthcare user-reported data?

The interviews revealed that mandating the use of patient data, as well as the practice of using it in professional activities, are two critical components. On the one hand, the organization’s external obligation is a factor that positively influences the application of patient-reported data in work activities just because it makes it a mandatory activity. This can encourage even the most sceptical public servants to use these data. On the other side, the professionals need to appreciate the use of these data for this practice to become habitual because “they are relevant to my work”, “they serve for own working activities”. A cultural factor emerged in the words of informants, underlining the need to really persuade public servants to understand

the value and the power of these data for improving and informing their decision-making processes.

The informants emphasized again the need of digital platforms and systems for supporting the use of these data to become a habit: “a good IT system, automated, is crucial to the long-term success and the sustainability of continually collecting”.

5.6. Is perceived security a determinant factor for the use of healthcare user-reported data?

Interviews confirmed that perceived security is a determining factor when it comes to the use of patient-reported data. User-reported data must be collected, reported, and shared securely. The informants highlighted the need of secure the digital tools for collecting and reporting these data, as well as the need to be compliant with data protection and privacy laws. Informants reported a concern about the proper safeguard of such data. This emerged as particularly important when informants discussed about user-reported outcomes of the public healthcare service, which of course relate to quality of life and health-related aspects that may be very sensitive information. These considerations may result in the implementation of additional protective measures that have always been deemed legitimate by the informants but have sometimes been cited as barriers to the collection and use of such data. In their point of view, this could further incentivize managers and professionals to opt for handling data that are simpler to collect and manage, potentially resulting in inequities or distortions.

This aspect implied the reflection on the different ways that can support a compliant data collection, storage and use in this delicate public sector, stressing the importance of digitalizing the tools along the data management chain: “the paper-based collection is the least secure”.

5.7. Is trust a determinant factor for the use of healthcare user-reported data?

Trust in user-reported data appears a key determinant. More specifically, knowing that user-reported

data is high-quality and well-validated information is an important consideration: “*Managerial team can make decisions knowing that the information is accurate and relevant*”.

Participants also underlined that data must be able to be translated into actions and play a supporting role in the good provision of services, and managerial decisions. This moves the trust on the level of potential impact of a data-driven public sector, since this approach support a more inclusive and trusted design, delivery and monitoring of public policies and services through the management, sharing and use of these data.

5.8. *Is anxiety a determinant factor for the use of healthcare user-reported data?*

According to interviewees, not feeling comfortable using patient input can be a barrier. This concern is especially appropriate “*for those who do not use the data*” and are unfamiliar with them.

The items used to define the factors were slightly modified based on the results of the interviews. The informants suggested to further investigate how the importance of the different factors above-mentioned can vary for different data-users or decision-makers, and for different user-reported data types. They also emphasized again the potential role that different types of digital platforms can play in determining the impact of these factors, since they were using different digital tools for user-reported data collection, monitoring and consultation, both in Wales and Italy.

6. DISCUSSION

Data-driven decision-making is fundamental for modernizing public administration. The digital transformation generates vast amounts of data and promotes their intensive use, presenting both opportunities and challenges for public organizations in creating public value. Despite growing recognition of the benefits of data-driven decision-making, public sector organizations often face internal resistance to adopting data-based practices. Similar to earlier waves of digital transformation, efforts to embed data use in daily administrative work are sometimes hindered by low adoption rates among public servants. This reluctance can stem from a variety of factors, including lack of trust in data, insufficient skills, or entrenched organizational routines. As seen in the e-government literature (Abdul Wahi & Berényi, 2023), such barriers have prompted a substantial body of research focused on understanding why public employees may hesitate to adopt new technologies or data tools. Building on this insight, it is important to explore the determinants that influence the adoption and use of data among public servants, as their engagement is crucial to realizing the full potential of data-driven innovation in the public sector.

Given the specific context of the public sector and critiques of traditional technology acceptance models – originally developed for private settings – for their possible limited applicability in government (Salama & Farag, 2024), we did not rely solely on the core UTAUT constructs. Alongside performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh *et al.*, 2003; 2011; 2012; Cimperman *et al.*, 2016; Lee *et al.*, 2019), we included habit (Venkatesh *et al.*, 2012), trust (Venkatesh *et al.*, 2011), and perceived security and anxiety (Cimperman *et al.*, 2016). Our study incorporated human, technical, and organizational factors, as suggested by a recent systematic literature review on the adoption of e-government among public sector employees (Abdul Wahi & Berényi, 2023). Future research should also explore factors like accountability, transparency, and citizen engagement, which may be especially relevant in public settings.

Integrating the results of the study with the broader framework of data-driven decision-making in public administration – as we tried in the following lines

– underscores the complexities and opportunities associated with leveraging healthcare user-reported data.

Moreover, instead of seeking empirical generalizability, this study contributes to theory development by uncovering mechanisms and patterns that align with and enrich existing scholarly work on determinants of technology adoption. The originality of this study lies also in refining the conceptual understanding of the UTAUT models' constructs in the context of patient-reported data uptake. The conceptualization of data – specifically patient-reported data – as a form of technology within organizational and decision-making processes is one key aspect of this research work. This perspective is grounded in the broader definition of technology proposed by Baskerville and Myers (2002), which includes also rules, practices, and data-related processes. By framing data itself as a socio-technical artefact, the study highlights novel dynamics in how data is integrated, interpreted, and acted upon in decision-making processes of public healthcare organizations. This framing allows the study to open new theoretical and empirical pathways in understanding the technological character of data and its implications for healthcare management.

This construct-validating study provides an adapted version of the UTAUT model for investigating barriers and facilitators of user-reported data uptake in the decision-making processes of public servants. The revised questionnaire needs go through statistical validation to ensure the factors' validity. Specifically, a subsequent phase of this study will focus on data collection with the adapted questionnaire. Sophisticated analysis will be conducted to analyze the effect of these factors on the intention to use patient data of healthcare professionals and managers. Finally, a third part of the study will apply this methodology to the evaluation of different patient-data reporting systems.

This study refines existing theoretical frameworks by showing how performance expectancy is recognized by professionals as a key determinant for studying the use of healthcare user-reported data, which is consistent with the broader narrative on data-driven public administration. This aligns with the understanding that effective data use is essential to realizing public value through improved service delivery, as emphasized in data-driven frameworks that highlight the strategic role of data in public services (Ubaldi &

Okubo, 2020; Osborne, 2020). As digital transformation continues to generate vast amounts of data, the ability to effectively utilize this data and really affect practice is critical as also suggested by Androniceanu (2023). Participants in the study recognized that user-reported data is valuable for improving services and aligning them with user needs, a perspective that aligns with the OECD's definition of a data-driven public sector where data is seen as a strategic asset for policy-making and service design (Ubaldi & Okubo, 2020). The emphasis on using data to improve service delivery highlights the importance of integrating user perspectives into decision-making, which is central to modern public administration practices.

Effort expectancy, particularly regarding the ease of use of data collection and analysis tools, is another critical factor identified in the study to explore data-use. This finding aligns with the broader challenges in data-driven public administration, where technical tools and digital platforms play a crucial role by enabling accessibility and usability, key conditions for embedding data-driven practices within public organizations, making easier access, consultation, reading and interpretation. The study participants' focus on the ease of use of both the tools and the data itself reflects the need for intuitive digital solutions that streamline bureaucratic processes and reduce costs (Valle-Cruz & García-Contreras, 2023). This is particularly important in overcoming barriers to data adoption, as highlighted by van Ooijen, Welby, & Ubaldi (2019), who noted that technical infrastructure is essential for embedding data-driven practices within public organizations.

The study's findings on social influence emphasize the theoretical relevance of the constructs of organizational culture and peer support in promoting the use of healthcare user-reported data, as well as the existence of organizations and institutions external to the organization that may have an impact on the decisions of healthcare professionals. This is consistent with research by Choi *et al.* (2021) and Cantarelli *et al.* (2023), which underscores that the success of data-driven decision-making hinges not only on technical factors but also on organizational aspects such as stakeholder cooperation and a supportive culture. Indeed, this reinforces the data-driven public administration framework's view that organizational and institutional support are critical enablers for data use and value creation in the public sector. This finding is

also in line with the theories on innovation diffusion and dissemination in healthcare (Greenhalgh *et al.*, 2004), which underlines that different social networks within the organizations can powerfully influence the adoption of innovation in different ways. For instance, vertical networks are more effective for authoritative decisions, while horizontal ones are more effective for peer influence and support. Similarly, the study highlights that both managerial mechanisms and peer pressure can drive data usage, reinforcing the idea that fostering a data-driven culture requires both top-down support and grassroots engagement within organizations. In considering external influences, it is imperative to acknowledge the role of collaboration with research institutions and universities, as such partnerships can significantly drive innovation. Additionally, it is essential to recognize the critical importance of the political and policy context, which is characteristic of numerous public services, including healthcare services. Future studies could explore the interorganizational context as an additional dimension within the social influence construct. Our findings suggested an embryonic idea that peer pressure may be linked to reputational dynamics within a broader institutional network (i.e., national, regional, and local levels). As highlighted in the literature on the diffusion of innovation in healthcare (Greenhalgh *et al.*, 2004), both collaborative and competitive mechanisms among comparable or similar organizations can shape the decision to adopt new practices, tools, or behaviours. This influence becomes particularly significant when the innovation is widely perceived as “*the norm*” (Greenhalgh *et al.*, 2004, p.609) within the context – essentially, a form of interorganizational habit, as discussed later for organizational habit.

Within the organizational realm, the study identifies facilitating conditions, such as the availability of resources and infrastructure, as critical to the successful integration of user-reported data. This finding resonates with the broader literature on data governance in the public sector. Robust data governance structures are necessary to capitalize on the value of data across the public sector (Ubaldi & Okubo, 2020). Also the literature on innovation diffusion in healthcare highlights the relevance of formal dissemination programs among the facilitating conditions, but also the system readiness for change, which includes, among the other factors, dedicated time and resources (Greenhalgh *et al.*, 2004). The need for adequate

resources, including material and human resources, as well as time and knowledge, reflects the complex, non-linear approach required to embed data-driven practices within public organizations, as described by van Ooijen, Welby, & Ubaldi (2019). Without these facilitating conditions, the potential of data-driven decision-making to improve service delivery and innovation can be significantly diminished.

The study’s emphasis on the previously explored mechanism of habit formation highlights the importance of making the use of user-reported data a regular practice within public organizations. Mandating the use of such data and integrating it into routine activities can drive its adoption, even among those initially resistant. This aligns with the broader goal of institutionalizing data-driven practices within public administration, where sustained use of data is crucial for long-term success. Such habitual use supports the recursive value chain described by van Ooijen *et al.* (2019), where continuous data use reinforces data quality and organizational learning. The emphasis on digital platforms and automated systems as tools to support habitual data use reflects the ongoing digital transformation in the public sector, which aims to make data use both sustainable and scalable (Valle-Cruz & García-Contreras, 2023).

The study confirms theoretical frameworks integrating perceived security and trust, presenting them as fundamental to the effective use of healthcare user-reported data. Concerns about data security and privacy are critical in the public sector, where data governance must ensure compliance with data protection laws and ethical standards. This finding is particularly relevant in light of challenges related to data sharing, interoperability, and maintaining high standards of data quality, as noted by van Ooijen *et al.* (2019). Trust in the quality and relevance of data is essential for it to be used effectively in decision-making processes, a point emphasized by both the study participants and existing literature.

The study refines existing theoretical models with insights into the ethical considerations surrounding data use, such as the risk of over-surveillance and the potential for data collection to exacerbate inequalities, align with broader concerns in the literature. Ethical and privacy concerns tied to the use and sharing of data have been identified among the main challenges

in data application in the public sector (Fredriksson *et al.*, 2017; Redden, 2018). While data-driven decision-making can empower marginalized groups and improve service delivery (Hepburn, 2018), it also poses risks if not managed carefully, because some individuals may have low level of digital competencies especially when coping with grand adults (Vainieri *et al.*, 2023).

Privacy issues are perceived as relevant and critical, since they can create tensions among different values (i.e., data protection versus transparency or research-driven use of data). Adeoye and Ran (2023) characterized the relationship between transparency and privacy as a dilemma – where each option offers distinct benefits but also involves significant trade-offs – drawing on Smith and Lewis’s (2011) definition of a dilemma as a situation in which opposing choices both carry clear advantages and disadvantages. However, studies on this topic are still scarce and need to be investigated. Moreover, the study’s participants highlighted the importance of secure data practices and the need to balance the benefits of data use with its potential to create inequities or distortions, particularly in sensitive areas like healthcare. This reflects the broader discourse on process equity, where the ethical implications of data use must be carefully considered to avoid negative outcomes such as the “*chilling effect*” described by Brayne (2017). In this context, the increasing reliance on data-driven systems in public organizations generates important normative tensions. These dynamics raise ethical questions about who defines value, whose data is collected, and how it is interpreted and used – especially when applied in sectors like healthcare, education, or welfare. The tension lies in balancing the promise of innovation, efficiency and efficacy with principles of equity, accountability, and individual autonomy. Furthermore, these systems can shift normative expectations about public service work, making performance increasingly defined by measurable indicators while potentially marginalizing qualitative dimensions of care and professional judgment. This ethical and normative complexity is an essential consideration in the broader framework of data-driven decision-making, underscoring the need for public organizations to navigate these tensions to ensure equitable and trustworthy use of data.

Our results hold theoretical relevance for broader discussions on data-driven public administration and

management, supporting analytic generalization as framed by Venkatesh and colleagues who developed the UTAUT model and its extensions. This study is part of ongoing research that aims also to explore the use of different digital platforms in facilitating the use of patient-reported data. These future directions are crucial for understanding how to optimize the use of user-reported data in public healthcare and other sectors. In fact, the use of advanced digital platforms can enhance the efficiency and effectiveness of data-driven decision-making. The integration of experience and outcome measures, as well as the focus on patient-centered care, reflects the broader trend towards more personalized and responsive public services, as advocated by Moore (2012).

7. CONCLUSIONS AND IMPLICATIONS

This construct-validating study is the first phase of a research that aims to provide valuable insights into the factors that facilitate or hinder the utilization of user-reported data within healthcare organizations. This specific study aimed to develop and propose to academics and practitioners a tool for understanding the determinants of the use of patient-reported data by healthcare managers and professionals. To reach this aim, we conducted interviews in two different countries that have a long experience with patient-reported data.

Rather than aiming for statistical representativeness, given that empirical generalizability is not the study’s goal, this research adopts an analytic generalization approach, aiming to generate theoretical insights that enhance understanding and inform future research on data-driven decision-making in public healthcare. Following Eisenhardt (1989), our analysis contributes to theory by confirming the importance of the hypothesized factors as the main determinants of the use of patient-reported data within healthcare organizations. This insight can be useful to stimulate the use of these measures by managers and healthcare professionals and overcome barriers to adoption.

The findings of this study reinforce theoretical propositions regarding the importance of several

determinants in the successful adoption of healthcare user-reported data in public administration. These determinants – performance expectancy, effort expectancy, social influence, facilitating conditions, habit, perceived security, trust and anxiety – are all critical in fostering a data-driven culture within public organizations.

Integrating these factors into data governance strategies for supporting the use of data in public organizations appears essential for modernizing public administration and realizing the full potential of data-driven decision-making to improve service delivery, innovation, and public value creation.

The integration of the study's findings with existing theories on data-driven public administration highlights the multifaceted challenges and opportunities associated with the use of user-reported data. As digital transformation continues to reshape public administration, the successful integration of user-reported data will require a comprehensive approach that addresses both technical and organizational challenges. By understanding these determinants and investigating them with the model proposed in this study, public organizations can develop strategies to effectively leverage user-reported data, ultimately enhancing service quality, equity, and accountability in the public sector.

8. ETHICS

Approved by the Swansea University Faculty of Humanities and Social Sciences Research Ethics Sub-Committee.

[English translation by the authors]

BIBLIOGRAPHY

Abdul Wahid, N.S.; Berényi, L. (2023). Systematic Literature Review on Adoption of E-government among Employees in the Public Sector. *Proceedings of the Central and Eastern European eDem and eGov Days 2023*, 21-28.

Adeoye, O.; Ran, B. (2023). Government transparency: paradoxes and dilemmas. *Public Management Review*, 1-24. Online [URL: <https://doi.org/10.1080/14719037.2023.2181981>].

Alexopoulos, C.; Lachana, Z.; Androutsopoulou, A.; Diamantopoulou, V.; Charalabidis, Y.; Loutsaris, M.A. (2019). How Machine Learning is Changing e-Government. *Proceedings of the 12th International Conference on Theory and Practice of Electronic Governance*, 354-363. Online [URL: <https://doi.org/10.1145/3326365.3326412>].

Alfiani, H.; Aditya, S.K.; Lusa, S.; Sensuse, D.I.; Putro, P.A.W.; Indriasari, S. (2024). E-government issues in developing countries using TOE and UTAUT frameworks: A systematic review. *Policy & Governance Review*, 8(2), 169-191.

Androniceanu, A. (2023). The new trends of digital transformation and artificial intelligence in public administration. *Revista Administratie Si Management Public (RAMP)*, 40, 147-155.

Barcevičius, E.; Cibaitė, G.; Codagnone, C.; Gineikytė, V.; Klimavičiūtė, L.; Liva, G.; Matulevič, L.; Misuraca, G.; Vanini, I. (2019). Exploring Digital Government transformation in the EU Analysis of the state of the art and review of literature. *Publications Office of the European Union. Luxembourg*. Online [URL: <https://doi.org/10.2760/17207>].

Baron, M.-L.; Cros, S.; Vittoris de, R. (2023). The maturity of digital transformation in small municipalities: digital paperwork or proactive administration?. *Gestion et Management Public*, 11(4), 35-55. Online [URL: <https://doi.org/10.3917/GMP.114.0035>].

Batalden, M.; Batalden, P.; Margolis, P.; Seid, M.; Armstrong, G.; Opiari-Arrigan, L.; Hartung, H. (2016). Coproduction of healthcare service. *BMJ Quality & Safety*, 25(7), 509-517. Online [URL: <https://doi.org/10.1136/BMJQS-2015-004315>].

Berry, L.L. (2019). Service innovation is urgent in healthcare. *AMS Review*, 9(1-2), 78-92. Online [URL: <https://doi.org/10.1007/s13162-019-00135-x>].

Berry, L.L.; Davis, S.W.; Wilmet, J. (2015). When the customer is stressed. *Harvard Business Review*, 93(10), 86-94.

Bevan, G.; Karanikolos, M.; Exley, J.; Nolte, E.; Connolly, S.; Mays, N. (2014). *The four health systems of the United Kingdom: how do they compare?*. Online [URL: www].

nuffieldtrust.org.uk/compare-uk-healthwww.health.org.uk/compareUKhealth].

Brayne, S. (2017). Big Data Surveillance: The Case of Policing. *American Sociological Review*, 82(5), 977-1008. Online [URL: https://doi.org/10.1177/0003122417725865/ASSET/IMAGES/LARGE/10.1177_0003122417725865-FIG6.JPEG].

Brundage, M.; Blazeby, J.; Revicki, D.; Bass, B.; De Vet, H.; Duffy, H.; Efficace, F.; King, M.; Lam, C.L.K.; Moher, D.; Scott, J.; Sloan, J.; Snyder, C.; Yount, S.; Calvert, M. (2013). Patient-reported outcomes in randomized clinical trials: Development of ISOQOL reporting standards. *Quality of Life Research*, 22(6), 1161-1175. Online [URL: <https://doi.org/10.1007/S11136-012-0252-1/TABLES/5>].

Cantarelli, P.; Belle, N.; Hall, J.L. (2023). *Information use in public administration and policy decision-making: A research synthesis*. Online [URL: <https://doi.org/10.1111/puar.13735>].

Caseau, Y. (2022). The Lean Approach to Digital Transformation: From Customer to Code and From Code to Customer. In *The Lean Approach to Digital Transformation: From Customer to Code and From Code to Customer*. Productivity Press. Online [URL: <https://www.taylorfrancis.com/books/mono/10.4324/9781003272816/lean-approach-digital-transformation-yves-caseau>].

Choi, Y.; Gil-Garcia, J.R.; Burke, G.B.; Costello, J.; Werthmuller, D.; Aranay, O. (2021). Towards Data-Driven Decision-Making in Government: Identifying Opportunities and Challenges for Data Use and Analytics. *Proceedings of the Annual Hawaii International Conference on System Sciences*, 2020-January, 2183-2192. Online [URL: <https://doi.org/10.24251/HICSS.2021.268>].

Cimperman, M.; Makovec Brenčič, M.; Trkman, P. (2016). Analyzing older users' home telehealth services acceptance behavior-applying an Extended UTAUT model. *International Journal of Medical Informatics*, 90, 22-31. Online [URL: <https://doi.org/10.1016/j.ijmedinf.2016.03.002>].

Codagnone, C.; Liva, G.; Barcevičius, E.; Misuraca, G.; Klimavičiūtė, L.; Benedetti, M.; Vanini, I.; Vecchi, G.; Ryan Gloinson, E.; Stewart, K.; Hoorens, S.; Gunashekar, S. (2020). *Assessing the impacts of digital government transformation in the EU: conceptual framework and empirical case studies*. Luxembourg: Publications Office of the European Union.

Coulter, A.; Lcock, L.; Ziebland, S.; Calabrese, J. (2014). Collecting data on patient experience is not enough: they must be used to improve care. *BMJ*, 348. Online [URL: <https://doi.org/10.1136/BMJ.G2225>].

Creswell, J.W.; Poth, C.N. (2016). *Qualitative inquiry*

and research design: Choosing among five approaches. Sage publications.

Da Silva, E. (2021). Customer Experience Project: A Framework to Create and Deliver Value to Customers. *International Journal of Marketing Studies*, 13(3). Online [URL: <https://doi.org/10.5539/ijms.v13n3p21>].

De Rosis, S.; Cerasuolo, D.; Nuti, S. (2020). Using patient-reported measures to drive change in healthcare: The experience of the digital, continuous and systematic PREMs observatory in Italy. *BMC Health Services Research*, 20(1), 1-17. Online [URL: <https://doi.org/10.1186/s12913-020-05099-4>].

De Rosis, S.; Ferrè, F.; Pennucci, F. (2022). Including patient-reported measures in performance evaluation systems: Patient contribution in assessing and improving the health-care systems. *International Journal of Health Planning and Management*, 37, 144-165. Online [URL: <https://doi.org/10.1002/hpm.3596>].

De Rosis, S.; Pennucci, F.; Lungu, D.A.; Manca, M.; Nuti, S. (2021). A continuous PREMs and PROMs Observatory for elective hip and knee arthroplasty: study protocol. *BMJ Open*, 11, 49826. Online [URL: <https://doi.org/10.1136/bmjopen-2021-049826>].

De Rosis, S.; Pennucci, F.; Nuti, S. (2019). From Experience and Outcome Measurement to the health Professionals' Engagement. *Micro & Macro Marketing*, 28(3), 493-520.

Denscombe, M. (2017). *The good research guide: For small-scale social research projects*. McGraw-Hill Education (UK) [ebook].

Donatini, A. (2020). The Italian health care system. *International Profiles of Health Care Systems*, 117.

Dunleavy, P.; Margetts, H.; Bastow, S.; Tinkler, J.; Barzelay, M.; Cox, C.; John, P.; Lownes, V.; Matheson, A.; Pinault, L.; Stoker, G.; Wehner, J.; Whittaker, S. (2006). New Public Management Is Dead-Long Live Digital-Era Governance. *Journal of Public Administration Research and Theory*, 16(3), 467-494. Online [URL: <https://doi.org/10.1093/jopart/mui057>].

Eisenhardt, K.M. (1989). Building Theories from Case Study Research. *Academy of Management Review*, 14(4), 532-550.

EIT Health (2020). *Implementing Value-Based Health Care in Europe: Handbook for Pioneers* (Director: Gregory Katz).

Ferrè, F.; de Rosis, S.; Murante, A.M.; Gilmore, K.J.; Ghilli, M.; Mariniello, D.; Nuti, S.; Roncella, M. (2021). Systematic and continuous collection of patient-reported outcomes and experience in women with cancer undergoing mastectomy and immediate breast reconstruction: a study protocol for the Tuscany Region (Italy). *BMJ Open*, 11(1), e042235. Online

[URL: <https://doi.org/10.1136/BMJOPEN-2020-042235>].

Ferreira, A.; Otley, D. (2009). The design and use of performance management systems: An extended framework for analysis. *Management Accounting Research*, 20(4), 263-282. Online [URL: <https://doi.org/10.1016/J.MAR.2009.07.003>].

Flott, K.M.; Graham, C.; Darzi, A.; Mayer, E. (2017). Can we use patient-reported feedback to drive change? The challenges of using patient-reported feedback and how they might be addressed. *BMJ Quality & Safety*, 26(6), 502-507. Online [URL: <https://doi.org/10.1136/BMJQS-2016-005223>].

Fredriksson, C.; F. Mubarak, F.; Tuohimaa, M.; Zhan, M. (2017) Big data in the public sector: A systematic literature review. *Scandinavian Journal of Public Administration*, 21(3), 39-62.

Gilmore, K.J.; Pennucci, F.; De Rosis, S.; Passino, C. (2019). Value in Healthcare and the Role of the Patient Voice. *Healthcare Papers*, 18(4), 28-35.

Gleeson, H.; Calderon, A.; Swami, V.; Deighton, J.; Wolpert, M.; Edbrooke-Childs, J. (2016). Systematic review of approaches to using patient experience data for quality improvement in healthcare settings. *BMJ Open*, 6(8), e011907. Online [URL: <https://doi.org/10.1136/bmjopen-2016-011907>].

Godlee, F. (2017). Are you ready for “collaborative health”? *BMJ*, 358. Online [URL: <https://doi.org/10.1136/bmj.j3257>].

Greenhalgh, T.; Robert, G.; Macfarlane, F.; Bate, P.; Kyriakidou, O. (2004). Diffusion of innovations in service organizations: systematic review and recommendations. *The Milbank Quarterly*, 82(4), 581-629.

Guest, G.; Bunce, A.; Johnson, L. (2006). How Many Interviews Are Enough?. *Field Methods*, 18(1), 59-82. Online [URL: <https://journals.sagepub.com/doi/10.1177/1525822X05279903>].

Håkansson Eklund, J.; Holmström, I.K.; Kumlin, T.; Kaminsky, E.; Skoglund, K.; Högländer, J.; Sundler, A.J.; Condén, E.; Summer Meranius, M. (2019). “Same same or different?” A review of reviews of person-centered and patient-centered care. *Patient Education and Counseling*, 102(1), 3-11. Online [URL: <https://doi.org/10.1016/J.PEC.2018.08.029>].

Hepburn, P. A. (2018). A New Governance Model for Delivering Digital Policy Agendas: A Case Study of Digital Inclusion Amongst Elderly People in the UK. *International Journal of E-Planning Research (IJEPR)*, 7(3), 36-49. Online [URL: <https://doi.org/10.4018/IJEPR.2018070103>].

Herxheimer, A.; Goodare, H. (1999). Who are you, and who are we? Looking through some key words. *Health Expectations*, 2(1), 3-6. Online [URL: <https://doi.org/10.1046/J.1369-6513.1999.00034.X>].

Holmlund, M.; Van Vaerenbergh, Y.; Ciuchita, R.; Raval, A.; Sarantopoulos, P.; Ordenes, F.V.; Zaki, M. (2020). Customer experience management in the age of big data analytics: A strategic framework. *Journal of Business Research*, 116(February), 356-365. Online [URL: <https://doi.org/10.1016/j.jbusres.2020.01.022>].

Johanssen, J.O.; Kleebaum, A.; Bruegge, B.; Paech, B. (2019). How do practitioners capture and utilize user feedback during continuous software engineering?. *Proceedings of the IEEE International Conference on Requirements Engineering*, 2019-Septe, 153-164. Online [URL: <https://doi.org/10.1109/RE.2019.00026>].

Kohnke, A.; Cole, M.L.; Bush, R. (2014). Incorporating UTAUT predictors for understanding home care patients' and clinician's acceptance of healthcare telemedicine equipment. *Journal of Technology Management and Innovation*, 9(2), 29-41. Online [URL: <https://doi.org/10.4067/S0718-27242014000200003>].

Lee, J.M.; Lee, B.; Rha, J.Y. (2019). Determinants of mobile payment usage and the moderating effect of gender: Extending the UTAUT model with privacy risk. *International Journal of Electronic Commerce Studies*, 10(1), 43-64. Online [URL: <https://doi.org/10.7903/ijecs.1644>].

Lungu, D.A.; Pennucci, F.; De Rosis, S.; Romano, G.; Melfi, F. (2020). Implementing successful systematic Patient Reported Outcome and Experience Measures (PROMs and PREMs) in robotic oncological surgery – The role of physicians. *The International Journal of Health Planning and Management*, 35(3), 773-787. Online [URL: <https://doi.org/10.1002/HPM.2959>].

Manetti, S.; Guidotti, E.; Vola, F.; Vainieri, M. (2024). A systematic literature review of Real-World Evidence (RWE) on post-market assessment of medical devices. *Health Economics Policy and Law*. Online [URL: <https://doi.org/10.21203/RS.3.RS-2512986/V1>].

McCull-Kennedy, J.R.; Hogan, S.J.; Witell, L.; Snyder, H. (2017). Cocreative customer practices: Effects of health care customer value cocreation practices on well-being. *Journal of Business Research*, 70, 55-66. Online [URL: <https://doi.org/10.1016/j.jbusres.2016.07.006>].

Moore, M.H. (2012). *Recognizing public value*. Harvard University Press.

Murante, A.M.; Vainieri, M.; Rojas, D.; Nuti, S. (2014). Does feedback influence patient – professional communication? Empirical evidence from Italy. *Health Policy*,

116(2–3), 273–280. Online [URL: <https://doi.org/10.1016/j.healthpol.2014.02.001>].

Nguyen, H.; Butow, P.; Dhillon, H.; Sundaresan, P. (2021). A review of the barriers to using Patient-Reported Outcomes (PROs) and Patient-Reported Outcome Measures (PROMs) in routine cancer care. *Journal of Medical Radiation Sciences*, 68(2), 186–195. Online [URL: <https://doi.org/10.1002/JMRS.421>].

NHS Wales (2018). *Patients' NHS Wales experience. Welsh Health Circular (WHC/2018/042)*. Online [URL: <https://www.gov.wales/patients-nhs-wales-experience-whc2018042>].

NHS Wales (2024). *Value-Based Healthcare for Wales*. Retrieved September 11, 2024. Online [URL: <https://vbhc.nhs.wales/value-based-healthcare-for-wales/>].

NHS Wales (2020). *NHS Wales Annual Report 2019/20*.

Nuti, S.; Vola, F.; Bonini, A. (2016). Making governance work in the health care sector: evidence from a “natural experiment” in Italy. *Health Economics, Policy and Law*, 11, 17–38. Online [URL: <https://doi.org/10.1017/S1744133115000067>].

OECD (2019). *State of Health in the EU: Italy Country Health Profile*.

Osborne, S. (2020). *Public service logic: Creating value for public service users, citizens, and society through public service delivery*. Routledge.

Osborne, S.P. (2018). From public service-dominant logic to public service logic: are public service organizations capable of co-production and value co-creation?. *Public Management Review*, 20(2), 225–231.

Osborne, S.P.; Radnor, Z.; Strokosch, K. (2016). Co-Production and the Co-Creation of Value in Public Services: A suitable case for treatment?. *Public Management Review*, 18(5), 639–653. Online [URL: <https://doi.org/10.1080/14719037.2015.1111927>].

Pai, Y.P.; Chary, S.T. (2013). Dimensions of hospital service quality: a critical review Perspective of patients from global studies. *International Journal of Health Care Quality Assurance*, 26(4), 308–340. Online [URL: <https://doi.org/10.1108/09526861311319555>].

Parasuraman, A.; Zeithaml, V.A.; Berry, L.L. (1988). SERVQUAL: A multiple-Item Scale for measuring consumer perceptions of service quality. *Journal of Retailing*, 64(1), 12. Online [URL: https://www.researchgate.net/publication/225083802_SERVQUAL_A_multiple-Item_Scale_for_measuring_consumer_perceptions_of_service_quality].

Parasuraman, A.; Zeithaml, V.A.; Berry, L.L. (1994). Reassessment of expectations as a comparison standard in measuring service quality: implications for further research. *Journal of Marketing*, 58(1), 111–124. Online [URL: <https://doi.org/10.1177/002224299405800109>].

Patton, M.Q. (2014). *Qualitative research & evaluation methods: Integrating theory and practice*. Sage publications.

Pennucci, F.; De Rosis, S.; Passino, C. (2020). Piloting a web-based systematic collection and reporting of patient-reported outcome measures and patient-reported experience measures in chronic heart failure. *BMJ Open*, 10, 37754. Online [URL: <https://doi.org/10.1136/bmjopen-2020-037754>].

Porter, I.; Gonçalves-Bradley, D.; Ricci-Cabello, I.; Gibbons, C.; Gangannagaripalli, J.; Fitzpatrick, R.; Black, N.; Greenhalgh, J.; Valderas, J.M. (2016). Framework and guidance for implementing patient-reported outcomes in clinical practice: Evidence, challenges and opportunities. *Journal of Comparative Effectiveness Research*, 5(5), 507–519. Online [URL: <https://doi.org/10.2217/ceer-2015-0014>].

Prahalad, C.K.; Ramaswamy, V. (2004a). Co-creating unique value with customers. *Strategy & Leadership*, 32(3), 4–9. Online [URL: <https://doi.org/10.1108/10878570410699249>].

Prahalad, C.K.; Ramaswamy, V. (2004b). Co-creation experiences: The next practice in value creation. *Journal of Interactive Marketing*, 18(3), 5–14. Online [URL: <https://doi.org/10.1002/dir.20015>].

Redden, J. (2018) Democratic governance in an age of datafication: Lessons from mapping government discourses and practices. *Big Data & Society*, 5(2), 1–13.

Richards, T.; Montori, V.M.; Godlee, F.; Lapsley, P.; Paul, D. (2013). Let the patient revolution begin. *BMJ*, 346. Online [URL: <https://doi.org/10.1136/BMJ.F2614>].

Rouidi, M.; Elouadi, A.E.; Hamdoune, A.; Choujtani, K.; Chati, A. (2022). TAM-UTAUT and the acceptance of remote healthcare technologies by healthcare professionals: A systematic review. *Informatics in Medicine Unlocked*, 32, 101008. Online [URL: <https://doi.org/10.1016/j.imu.2022.101008>].

Ruijter, E.; Porumbescu, G.; Porter, R.; Piotrowski, S. (2023). Social equity in the data era: A systematic literature review of data-driven public service research. *Public Administration Review*, 83(2), 316–332. Online [URL: <https://doi.org/10.1111/PUAR.13585>].

Salama, M.; Farag, R. (2024). A Comprehensive Review of Technology Acceptance Models in the Context of Digital Government Services. In *2024 International Conference on Decision Aid Sciences and Applications (DASA)*. IEEE, 1–9.

- Slade, E.L.; Williams, M.; Dwivedi, Y.; Sudbury, D.; Saeed, A.; Nnajiuba, U.; Muruges-Warren, A.; Mashayekhi, S.; Abdel-Gadir, S.; Dubb, S.; Caris, J.; Cox, B. (2013). An extension of the UTAUT2 in a healthcare context. *UK Academy for Information Systems Conference Proceedings 2013*, 55. Online [URL: <https://aisel.aisnet.org/ukais2013/55/>].
- Smith, W.K.; Lewis, M.W. (2011). Toward a theory of paradox: a dynamic equilibrium model of organizing. *Academy of Management Review*, 36(2), 381-403. Online [URL: <https://doi.org/10.5465/amr.2011.59330958>].
- Snyder, C.F.; Aaronson, N.K. (2009). Use of patient-reported outcomes in clinical practice. *The Lancet*, 374(9687), 369-370. Online [URL: [https://doi.org/10.1016/S0140-6736\(09\)61400-8](https://doi.org/10.1016/S0140-6736(09)61400-8)].
- Tseng, E.K.; Hicks, L.K. (2016). Value Based Care and Patient-Centered Care: Divergent or Complementary?. *Current Hematologic Malignancy Reports*, 11(4), 303-310. Online [URL: <https://doi.org/10.1007/S11899-016-0333-2/TABLES/1>].
- Ubaldi, B.; Okubo, T. (2020). *OECD Digital Government Index (DGI): Methodology and 2019 results*. Online [URL: <https://www.oecd-ilibrary.org/content/paper/b00142a4-en>].
- Vainieri, M.; De Rosis, S.; Nuti, S.; Spataro, V.; Donata Bellentani, M.; Carbone, S.; Quattrone, F.; Visca, M.; Urbani, A. (2022). Da un'iniziativa internazionale a un osservatorio nazionale per monitorare l'esperienza dei pazienti cronici in Italia. *Sistema Salute*, 66(2), 120-138. Online [URL: <https://doi.org/10.48291/SISA.66.2.2>].
- Vainieri, M.; Vandelli, A.; Benvenuti, S.C.; Bertarelli, G. (2023). Tracking the digital health gap in elderly: A study in Italian remote areas. *Health Policy*, 133, 104842. Online [URL: <https://doi.org/10.1016/J.HEALTHPOL.2023.104842>].
- Valle-Cruz, D.; García-Contreras, R. (2023). *Towards AI-driven transformation and smart data management: Emerging technological change in the public sector value chain*. Online [URL: <https://doi.org/10.1177/09520767231188401>].
- Van Ooijen, C.; Ubaldi, B.; Welby, B. (2019). *A data-driven public sector: Enabling the strategic use of data for productive, inclusive and trustworthy governance*. Online [URL: <https://doi.org/10.1787/09ab162c-en>].
- Venkatesh, V.; Morris, M.G.; Davis, G.B.; Davis, F.D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478.
- Venkatesh, V.; Thong, J.Y.L.; Chan, F.K.Y.; Hu, P.J.H.; Brown, S.A. (2011). Extending the two-stage information systems continuance model: Incorporating UTAUT predictors and the role of context. *Information Systems Journal*, 21(6), 527-555. Online [URL: <https://doi.org/10.1111/J.1365-2575.2011.00373.X>].
- Venkatesh, V.; Thong, J.Y.L.; Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, 36(1), 157-178.
- Voorberg, W.H.; Bekkers, V.J.J.M.; Tummers, L.G. (2014). Public Management Review A Systematic Review of Co-Creation and Co-Production: Embarking on the social innovation journey. *Public Management Review*, 17(9), 1333-1357. Online [URL: <https://doi.org/10.1080/14719037.2014.930505>].
- Wang, H.; Tao, D.; Yu, N.; Qu, X. (2020). Understanding consumer acceptance of healthcare wearable devices: An integrated model of UTAUT and TTF. *International Journal of Medical Informatics*, 139, 104156. Online [URL: <https://doi.org/10.1016/J.IJMEDINF.2020.104156>].
- Withers, K.; Palmer, R.; Lewis, S.; Carolan-Rees, G. (2021). First steps in PROMs and PREMs collection in Wales as part of the prudent and value-based healthcare agenda. *Quality of Life Research*, 30(11), 3157-3170. Online [URL: <https://doi.org/10.1007/S11136-020-02711-2/FIGURES/3>].

APPENDIX

Questionnaire in English: factors and survey items used to measure the different factors (1/3)

| | |
|---|--|
| Performance expectancy: the degree to which healthcare professionals and managers believe that using patient feedback will help them to perform their job better. | |
| PE1 | I (would) find patient-reported measures useful in my job. |
| PE2 | The use of patient-reported measures (would) enables me to accomplish tasks more quickly. |
| PE3 | The use of patient-reported measures (would) makes it easier for me to accomplish tasks. |
| PE4 | The use of patient-reported measures (would) improves my productivity. |
| PE5 | The use of patient-reported measures (would) enhances my effectiveness in accomplishing tasks. |
| Effort Expectancy: the degree of ease associated with the use of patient feedback. | |
| EE1 | (I expect) The patient-reported measures are clear and understandable |
| EE2 | (I expect) The patient-reported measures are easy to use in my working activities |
| Social Influence: the degree to which healthcare providers and managers perceive that other people, i.e., institutional bodies, senior management, colleagues and external bodies believe patient feedback should be used. | |
| SI1 | Institutional bodies (at different levels, for example national or regional) value the use of patient-reported measures. |
| SI2 | Institutional bodies (at different levels, for example national or regional) support the use of patient-reported measures. |
| SI3 | The senior management of my organization values the use of patient-reported measures. |
| SI4 | The senior management of my organization supports the use of patient-reported measures. |
| SI5 | My peers value the use of patient-reported measures. |
| SI6 | My peers support the use of patient-reported measures. |
| SI7 | External bodies value the use of patient-reported measures. |
| SI8 | External bodies support the use of patient-reported measures. |

APPENDIX

Questionnaire in English: factors and survey items
used to measure the different factors (2/3)

| Facilitating conditions: the degree to which participants believe that organizational resources are provided to support the use of patient feedback in healthcare organizations. | |
|--|---|
| FC1 | I (would) have the material resources necessary to use patient-reported measures. |
| FC2 | I (would) have the human resources (e.g., a team of people working with me) necessary to use patient-reported measures. |
| FC3 | I (would) have the time necessary to use patient-reported measures. |
| FC4 | I (would) have the knowledge necessary to use patient-reported measures. |
| FC5 | Patient-reported measures are complementary (would be complementary) to other measures I use (e.g., performance indicators, and clinical data). |
| FC6 | A specific person (or group) is available (or would be available) for assistance with difficulties with the use of patient-reported measures. |
| FC7 | Guidance, specialized instructions and/or training are available (or would be available) to me about the use of patient-reported measures. |
| Habit: the degree to which the use of patient feedback is expected in the organisation as well as how likely healthcare professionals and managers are to use them in their daily work. | |
| H1 | I am (or should be) required to use patient-reported measures in my practice. |
| H2 | It has become (could become) natural to me to use patient-reported measures in my practice. |
| H3 | It is (I expect it would be) important to me to use patient-reported measures as much as possible in my practice. |
| Perceived Security: the degree to which patient feedback is collected, reported and shared securely and in line with privacy law. | |
| PS1 | I am confident that patient-reported measures are collected securely and in line with privacy law. |
| PS2 | I am confident that patient-reported measures are reported securely and in line with privacy law. |
| PS3 | I am confident that patient-reported measures are shared securely and in line with privacy law. |
| PS4 | The patient-reported measures offer a secure means through which to access information without accessing(necessarily) sensitive personal information. |

APPENDIX

Questionnaire in English: factors and survey items used to measure the different factors (3/3)

| | |
|---|---|
| Trust: the degree to which healthcare professionals and managers value the use of patient-reported measures in their practice and their role in supporting good service delivery and managerial decisions. | |
| T1 | The patient-reported measures are high-quality and well-validated data. |
| T2 | I value the use of patient-reported measures. |
| T3 | The patient-reported measures perform their role of supporting the good provision of services. |
| T4 | The patient-reported measures perform their role of supporting managerial decisions. |
| Anxiety: in terms of confidence in the use of these data and/or any platforms reporting these data. | |
| A1 | I don't (I would not) feel comfortable in using patient-reported measures. |
| A2 | I am not (I would not feel) confident in using patient-reported measures for fear of unexpected consequences. |
| A3 | I feel patient-reported measures are necessary data in both educational and work settings. |
| Intention to use: the degree to which an individual intends to use patient feedback in their working activities in healthcare | |
| IU | I intend to (continue to) use patient-reported measures in the future. |

Notes: PE: performance expectancy, EE: effort expectancy, SI: social influence,
 FC: facilitating conditions, H: habit, PS: perceived security, T: trust, A: Anxiety, IU: intention to use.