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From chalk to clicks – The impact of (rapid) technology adoption on employee emotions in the higher education sector

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ABSTRACT

Drawing on Appraisal Theory, this study explores the psychological impact of technology adoption during the first year of the COVID-19 pandemic on UK Higher Education (HE) employees. Using sentiment analysis, we analyse approximately 9000 tweets focusing on technology use in UK HE between March 2020 and February 2021, leading to the identification of significant changes in perceptions and feelings. Followingly, we undertake 52 in-depth online qualitative surveys (employing a laddering approach) from UK HE employees to better understand the emotional and psychological consequences of technology adoption. The results highlight four distinct phases based on the functional and emotional impact of technology: secure, scrutinize, streamline, and sustain. We observe that several distinct positive (e.g., empowerment and self-efficacy), and negative (e.g., isolation and stress) psychological consequences emerge in each phase, which are concomitant with the transition from an emergency/rapid to planned/proactive technology adoption and integration. This study offers a framework demonstrating the impact of technology adoption on employee emotions and how these emotions change during the transition from rapid to planned technology adoption. Thus, given the importance of emotions within organizations, the implications of our work offer valuable insights for organizations transitioning from emergency to planned technology adoption in the future.

1. Introduction

In the context of global pandemics and epidemics, the COVID-19 crisis has brought about one of the most historically noteworthy, rapid, and forced changes to the behaviour of individuals in many societies (Pillay, 2021). Over a period of two months in early 2020, many countries used legal powers to prevent citizens from leaving their homes, predominantly relying on technology to work, socialize, and relax. Throughout society, this rapid change had a profound psychological impact, effecting the mental health of individuals (Serafini et al., 2020), the ways that businesses operate and, by extension, the global economy (Sarkodie and Owusu, 2021). Within peoples' working lives, there has been significant disruption and an increased dependence upon technology to sustain industries. In this paper we focus on the Higher Education (HE) sector in the United Kingdom, to explore the psychological impact of this (rapid) technology adoption.

Unlike other industries, UK HE can be considered a more 'traditional' sector, with a somewhat antiquated approach to technology adoption. Despite many universities claiming to be technologically advanced, prior to the pandemic, face-to-face teaching and physical engagement and processes remained an important part of their operations and the learning experience they strive to offer (Daumiller et al., 2021; Thomas, 2020). The COVID-19 pandemic rapidly and radically changed the way technological innovation was adopted and used in the HE sector. During the first months of the pandemic, many innovative solutions were swiftly introduced, enabling HE institutions to maintain their operations while striving to retain an offer which was valuable. Nevertheless, these developments have been received with scepticism by many key stakeholders, including students and university staff, not least with regard to quality and value, but also the psychological impact resulting from the rapid adoption of these innovative solutions (e.g., Bedenlier et al., 2020; Oliveira et al., 2021).

In the HE learning and teaching context, scholars are keen to highlight the different approaches to online teaching. Rapanta et al. (2021) remind us of the distinction between emergency remote teaching (ERT) and online learning and teaching (OLT), in that the former is, by

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definition, reactive and a temporary shift; there is a lack of preparation before the teaching is undertaken (Hodges et al., 2020). By contrast, OLT is far more planned and carefully designed to combine a range of pedagogical tools (e.g., synchronous, asynchronous, and independent study activities) (Anderson, 2008). While the future vision for HE in terms of the balance between face-to-face and OLT is still being debated, there is growing consensus that 'normal' (i.e., pre-pandemic) practices need to be updated (Roy, 2020).

Several recent studies examine the impact of the pandemic on the HE sector from the perspectives of both staff and students within specific countries or regions (e.g., Ashour et al., 2021; Daniels et al., 2021; Daumiller et al., 2021; Marek et al., 2021; Scherer et al., 2021). Largely these studies find mixed, and in some cases, contradicting results in terms of confidence with technology. Moreover, some research (e.g., Iglesias-Pradas et al., 2021) reports that adopting technology facilitates positive impacts in teaching. Conversely, other studies (e.g., Aguilera-Hermida, 2020) find that the rapid transition to online learning is a negative experience for most students, due to issues such as limited interactions and self-motivation. Our paper is situated within this emerging narrative; however, it is unique because we focus specifically on the emotional and psychological impact that this technology adoption had on HE employees.

More specifically, the current study contributes to existing literature as it focuses on the under-researched area of the psychological and emotional impact of employee technology adoption. Although earlier studies investigate the impact of technology adoption on teaching and the student experience, to date very little research has focused on the impact of technology adoption on employee emotion. Therefore, our research aims to contribute to theory and practice of technology adoption in business, by exploring the emotional and psychological impact of rapid technology adoption on employees, and investigating how this has changed over time as technology adoption became more proactive and planned. To achieve this, employee perceptions regarding technology adoption in the HE sector in the UK are explored to identify any changes during the first year of the pandemic. Further, the nature and the drivers of these changes in perception are examined in more depth, to understand the functional and the psychological consequences of technology adoption.

Our study is very timely because there are significant pressures on educational institutions, as well as on organizations and businesses in other sectors (in the UK and elsewhere) regarding the adoption of technology, as a result of several factors, including the pandemic, Brexit,[1] and changes in customer preferences and behaviour. Thus, research on the psychological impact of technology adoption, both from an emergency/reactive perspective and a planned/ proactive perspective is key, as it provides organizations with a way to navigate these emergent challenges while considering the mental health and psychological wellbeing of employees, which can affect the performance of the organization as well as the satisfaction and retention of its employees. The remainder of this paper will be structured thus: in Section 2 we review the extant literature and theory that underpins our work. In Section 3 we explore the methods that have been employed, before presenting and discussing our findings in Sections 4 and 5 respectively. Finally, we conclude with the paper's key contributions and our theoretical model in Section 6.

2. Theory and literature review

Investment in IT technology has played both an emergency and a strategic role in the HE sector during the COVID-19 pandemic (Mittal et al., 2021; Rapanta et al., 2021), as employees were required to rapidly embrace and use digital technologies introduced by their institutions in order to continue engaging with their professional and academic activities. Nevertheless, technology adoption is not always followed by positive outcomes for the organization and its various stakeholders, including its customers and employees. The effectiveness of technology in supporting an organization's processes and goals is affected by several factors, such as the technical characteristics of the technology itself, but also employee-related factors including their knowledge, attitudes and emotions (Melián-González and Bulchand-Gidumal, 2017). From this perspective, a better understanding of employees' technology adoption offers clear benefits to managers and IT developers (Ramaswamy and Ozcan, 2018). As such, this paper explores the impact that introducing technology during the pandemic had on the emotions of UK HE employees, and how it has changed over time as organizations (and employees) had more time to reflect and strategically plan the use of technology in the workplace. The aim of the study is to explore these (positive and/or negative) emotions and how they may have changed over time, to enable the development of more effective technology adoption strategies within organizations.

2.1. Emotions and technology adoption

Over the past couple of decades, the role of emotions in the acceptance and adoption of technology has been acknowledged in academic literature. According to Bagozzi et al. (1999, p. 184) emotions can be defined as.

> a mental state of readiness that arises from cognitive appraisals of events or thoughts; has a phenomenological tone; is accompanied by physiological processes; is often expressed physically (e.g., in gestures, posture, facial features); and may result in specific actions to affirm or cope with the emotion, depending on its nature and meaning for the person having it.

Therefore, emotions are affected by specific events and situations that individuals face, and can influence their behaviour and the ways they react and adapt to the demands of their environment (Beaudry and Pinsonneault, 2010).

Researchers argue that in addition to the cognitive aspects of technology adoption, such as the ones explored through Affordance Theory (Gibson, 1979), the technology acceptance model (Davis, 1989), and the unified theory of acceptance and use of technology (Venkatesh et al., 2003), emotions can positively or negatively affect the use and adoption of technology (Brown et al., 2004; Venkatesh, 2000). For instance, researchers have indicated that feelings of excitement, arousal and pleasure can positively influence technology adoption (e.g., Hedman and Gimpel, 2010; Kourouthanassis et al., 2015), while fear and anxiety can negatively affect the willingness to use new technologies (Hohenberger et al., 2017; Venkatesh and Brown, 2001). Furthermore, in addition to their direct impact on the adoption of new technologies, emotions can also affect the rational evaluations of the perceived benefits and costs of technology, which can positively or negatively affect technology adoption (Featherman et al., 2021).

From an organizational perspective, research has demonstrated that when new technologies are introduced in an organization, employees can experience strong emotions that determine their adoption behaviours (e.g., Wood and Moreau, 2006). For example, Zheng and Montargot (2021) use Coping Theory to explain how employees and managers need to address anger and fear triggered by new technology in the workplace, as they can have significant negative effects on its long-term adoption. In their work, Stam and Stanton (2010) use elements of Regulatory Focus Theory and Affective Events Theory to investigate the relations between employee emotions and technology change in the workplace. The authors argue that employees' emotions surrounding the deployment of the new technology can affect their responses to technology adoption (e.g., resistance to change or rejecting the new system). More recently, Mamun et al. (2020) employ the Expectation–Confirmation Model to investigate IT use in the workplace, explaining that emotions are of paramount importance for the

[1] A portmanteau for Britain's exit from the European Union (EU).

employee's continued use of IT.

Despite the meaningful insights coming from this stream of research, extant literature suggests that emotions not only influence, but can also be influenced by, the use and adoption of technology. To date, however, only a limited number of studies examine how adoption of new technologies can trigger emotional reactions from users. Existing research indicates that adopting new technologies may result in different emotions and feelings; from rage, anxiety, anger, sadness, and desperation, to happiness and relief (Kay and Loverock, 2008; Pozón-López et al., 2021). Lee et al. (2011) use Mehrabian and Russell's (1974) Stimulus-Organism-Response framework to explain how evaluating the attributes of high-technology products can result in positive emotions such as pleasure and arousal. Additionally, Manika et al. (2021) describe how adopting pro-environmental technologies can trigger the feeling of pride, and influence conservation behaviours. On the other hand, Marikyan et al. (2020) explain how negative disconfirmation of expectations following use of technology can result in feelings of anger, guilt and regret, and trigger coping mechanisms aimed at subduing these negative emotions. In their research, Mick and Fournier (1998) identify an interesting paradox associated with the impact of technology adoption on emotions. The authors explain that although technology can facilitate feelings of control, freedom, competence, efficiency and fulfilment, in other cases it may have the opposite effect, as it enables individuals to realize needs that were previously unnoticed, and increases dependency on technology, which may result in feelings of disorder, incompetence, inefficiency and isolation.

From an organizational point of view, emotions have detrimental consequences for the employees as well as for the organization, including employee dissatisfaction and poor performance, work avoidance, lower work quality, and higher staff turnover (Cho et al., 2017; Moreo et al., 2020). Therefore, research on the impact of technology on employee emotions should feature more prominently in the technology adoption studies. To date, however, little research has focused on this aspect (Beare et al., 2020). Additionally, as technology adoption in HE during the pandemic was initially reactive, rapid and compulsory (due to lockdown and social distancing regulations) and mandated by the institutions (as they were introducing different technologies to support their day-to-day activities), employees were more restricted in their technology adoption and use, which may have affected the impact that this technology had on their emotions. Furthermore, studies suggest that emotions are not static but can change over time (Maguire and Geiger, 2015). This is also true in the context of technology adoption, as the impact of technology on users' emotions transcends the initial adoption of technology and may vary given their experiences and interaction with new technologies. This is particularly relevant in technology adoption during the pandemic, as employee emotions, following the rapid introduction of technology during the initial stages of the pandemic, may differ compared to the later evaluations of and emotional reactions to the more planned and strategic adoption, use and integration of these technologies within organizations. To date, however, there is very limited research on how employee emotions may change in the time following the initial adoption and use of new technologies in the working environment.

The above discussion presents a number of different theoretical ‘lenses’ which have been adopted in the past to explore the links between the use of technology and the users' emotions and feelings. Within our study, Appraisal Theory has been adopted as it can provide a meaningful lens to explore the impact of technology on emotions (positive and negative) not only at the early stages of the pandemic, but also later when the use of technology in HE was more planned and strategic. Appraisal Theory has been adopted by several studies in the past as one of the key theories to explore individuals' emotional responses to specific events. Unlike other theories that focus on negative emotions (e.g., Coping Theory), Appraisal Theory offers insights on how emotions (both positive and negative) are triggered, following an individual's appraisal, interpretation, and evaluation of a situation (Frijda et al., 1989; Lerner and Keltner, 2001; Roseman and Smith, 2001). More recently in technology adoption, several studies exploring the impact of emotions on technology adoption have used Appraisal Theory as an effective framework to explore the nuances underlying distinct emotional states (Ding, 2021; Zheng and Montargot, 2021).

According to Appraisal Theory, cognitive appraisals of emotions are based on a two-stage process: primary and secondary appraisals, which can result in discrete emotions (Frijda et al., 1989; Lazarus, 1991; Lerner and Keltner, 2001). These appraisals refer to: a) evaluating the consistency of the situation with the individual's motives, goals and wellbeing (primary evaluation); and b) the level of control that the individual has over the situation and outcomes (secondary evaluation). Therefore, positive emotions arise when individuals appraise a situation as goal-congruent: they believe that the situation or event will allow them to achieve their goals. On the other hand, negative emotions stem from goal-incongruent situations/events, which impede the potential of the individual to achieve their goals (primary appraisal), and also when the individual is concerned about their ability to control or cope with the situation (secondary appraisal).

In addition to the above, these primary and secondary evaluations can be continuous, that is, a situation may be repeatedly appraised and re-evaluated with respect to an individual's goals or level of control (Folkman and Lazarus, 1985; Scherer, 1993). Therefore, Appraisal Theory offers a useful approach to explore emotions not only in the initial stages of technology adoption but also in the longer-term. By employing Appraisal Theory our study addresses gaps in the existing literature by exploring employee evaluation and (primary and secondary) appraisal of technology adoption in HE, and the impact this appraisal has on their emotions over time, from emergency technology adoption during the first months of the pandemic, to the more planned and strategic adoption stages that followed.

To achieve our research objectives, this study employs an innovative, two-step methodological approach to collect and analyse data, combining sentiment and qualitative data analysis. This approach relied on unstructured data from social media coupled with sentiment analysis techniques and qualitative data to explore in-depth the emotional impact of technology adoption over a longer period of time. Details on our methodology are provided in the next section of our paper.

3. Methods

3.1. Overview

The storage and analysis of online content, into structured meaningful information, can provide valuable insights into people's perceptions, attitudes and behaviour (Devine et al., 2021; Jabbar et al., 2019). Currently, online data such as blogs, websites and social media information are rich sources of data which can be used to inform business strategies (Dahooie et al., 2021). However, as data becomes increasingly complicated and the need for data processing becomes a necessity (Jabbar et al., 2019; Liang and Liu, 2018), applying machine-learning techniques becomes imperative (Syam and Sharma, 2018). Extant literature suggests the use of sentiment analysis is gathering pace and many researchers utilize it to explore people's behaviour, perceptions and emotions in different contexts. For instance, Neogi et al. (2021) have employed sentiment analysis to understand the reactions of public farmers towards new laws imposed by the government, while Choi et al. (2020) develop an approach based on sentiment analysis to identify time-evolving product opportunities and manage customer complaints. Nevertheless, one of the limitations of existing research using sentiment analysis is that results are very quantitative and do not provide an in-depth analysis of the phenomena.

For our research, first we utilized sentiment analysis and text mining on user-generated content from Twitter (Wang et al., 2022), using a range of tools including Python and WordNet, to ascertain the links between technology adoption and emotions. Next, we launched an in-depth online qualitative survey to allow UK HE employees to provide more in-depth insights into the psychological and emotional impact of technology during our analysis time frame. We will now discuss these methods in more detail, before moving on to present our findings.

3.2. Step 1 – Sentiment analysis

Sentiment analysis is defined as a method (or process) to ascertain individual perceptions and/or behaviours as a positive or negative construct (Da Silva et al., 2014; Phan et al., 2020).

In this paper we view sentiment analysis as an essential tool in extracting information about perceptions, feelings and emotions relating to technology adoption in the UK HE sector. Within this, we use a corpus-based tool in Python to help analyse the data. The tool we utilize is WordNet and is hosted, maintained, and developed by Princeton University.[2] Utilizing corpus tools such as WordNet within sentiment analysis can offer meaningful insights into the perceptions, feelings and behaviours of different stakeholders and can potentially play an important role in the development of proactive, forward-thinking organizational strategies. As such, sentiment analysis has become an important tool among marketers and business practitioners to gauge consumer behaviour, understand brand reputation, and to develop social media analysis (Domingo et al., 2020; Liu, 2019).

Although there are many different platforms that individuals engage with to express their opinions, feelings and perceptions, Twitter has been recognized by earlier studies as a popular platform within academic and professional circles, as it is a commonly used platform to broadcast professional information, academic opinions and scientific tweets, rather than as a platform for personal communication and interactions among individuals (e.g. Neiger et al., 2013; Vainio and Holmberg, 2017; Yu et al., 2019). As such, it is a very popular platform within the target group of our study. Therefore, the choice of Twitter as the source of data for our sentiment analysis ensured access to substantial, relevant information from our target group: HE employees in the UK.

However, the development of sentiment within an organizational context is not without its challenges. Using Twitter as an example, from a technical perspective the issue of sentiment itself is problematic, as neutral tweets are very common and, in many scenarios, outweigh the positive and negative sentiment (Da Silva et al., 2014). Researchers also suggest that on some social media platforms, like Twitter, the user-generated content can be very short, thus creating limited sentiment cues and creating issues in developing relationships between data (Acker and Kreisberg, 2019; Kitchens et al., 2018). In the current research, by carefully selecting the filters, keywords and timeperiods examined, we tried to ensure that sufficient and relevant data were collected for our sentiment analysis, as described in the following section.

3.2.1. Preparing the data set

As previously outlined, sentiment analysis is designed to detect emotions, perceptions and opinions based on user context; this is achieved by classifying content into positive, negative or neutral categories. Data classification is a popular approach in organizing and shaping big data in preparation for analysis (García-Gil et al., 2017). As with all data sets there are limitations which are offset by the quality of the data, especially in relation to user activity and behaviour (van Dieijen et al., 2019). The volume of data being created and collected (on a daily basis) demonstrates the uniqueness of the data set, but also its complexity as an unstructured data source (Jabbar et al., 2019). Twitter offers breadth and depth of data, and combined with its ease of access and availability, it is an ideal source to conduct analysis from both B2B and B2C perspectives.

Thus, in this paper we utilized classification approaches to ascertain user sentiment through a Twitter data set. We downloaded the data set through *TweetBinder*, an online repository which harvests Twitter data via its Application Programming Interface (API). The key aspect of the data harvesting is the design of a search query which can provide a large enough data set to measure sentiment. To this end we utilized the Boolean Twitter query outlined in Fig. 1 to download the required user opinions.

This query was executed with date sequencing from 18th February 2020 (one month before the UK lockdown) until 12th July 2021, encompassing the lockdown period and the start of the vaccine rollout. The output of such an approach resulted in 9122 tweets being harvested. The authors subsequently undertook a process of cleaning the data by removing irrelevant and unnecessary information and old columns (Jabbar et al., 2019). The key variable at this point was creating a more concentrated data set which encompassed the lockdown period for the relevant target group in our study. Thus, we refined the data set to encompass tweets during 1st March 2020 until 28th February 2021, which resulted in 8396 tweets.

3.2.2. Approach to data cleansing

Sentiment analysis is a technical procedure, while Python is a popular coding language utilized by many software developers to conduct data analysis. While the data we have was rich in depth, dates, and content it still required data processing to get to a stage where sentiment could be ascertained. We outline the process in Fig. 2.

Thus, to extract sentiment from the data set we utilized Python 3.9 with the Spyder 5.0.5 Integrated Development Environment (IDE). To organize and prepare the data set we utilized NLTK 3.6.3 (Natural Language Toolkit) which includes the WordNet lexical database. The NLTK is an open-source tool which is equipped with a suite of libraries and programmes for processing the English language within Python. The WordNet database encompasses a corpus module, available to individuals to develop sentiment. In Python we imported the necessary libraries required for the first stage of the data processing by importing NLTK and CSV (comma-separated values). These two methods allowed the authors to import the data from a CSV file into a Python list.

The next stage of the process was to tokenize the text into meaningful smaller values. Tokenization is crucial in separating the tweets (which are imported as paragraphs) into smaller portions for easier analysis and depth. These smaller portions are referred to as tokens and can be analysed in a more logical manner. However, even after tokenization the volume of data remained high; this included data which had limited value, and thus needed to be removed. Accordingly, the next stage in the data processing was to remove 'stop words' from the data set. A stop word is defined as a common word (e.g., determiners such as 'the' and 'an') which has no real meaning to the overall sentiment. They can occupy a significant amount of space in the running of the code; subsequently, an increased volume of stop words, within a large data set, can cause 'run time' issues when executing. NLTK has a stop word import facility (from *nltk.corpus import stopwords*) allowing the author to conduct a 'running test' on the data and remove words which can encumber sentiment. The remaining data was then cleaned for 'noise reduction' in the form of hashes and URLs using 'ReGex', a regular expression in Python which is used to detect patterns. The data were then ready for the sentiment analysis using NTLK and WordNet.

3.3. Step 2 - online qualitative survey

Although the sentiment analysis allowed for exploring HE employees' perceptions and feelings towards technology adoption and identifying any changes during the first year of the pandemic, a more in-depth investigation was required to enable a better understanding of these perceptions (positive or negative), and the psychological and emotional factors that influenced them, as well as the drivers behind any changes in employee emotions.

In order to explore the depth of impact of rapid technology adoption,

[2] See https://wordnet.princeton.edu/

#HigherEducation ***OR*** *#HE* ***OR*** *#BlendedLearning* ***OR*** *#HybridLearning* ***AND*** *#Covid* ***OR*** *#Covid19*

Fig. 1. Boolean Twitter query.

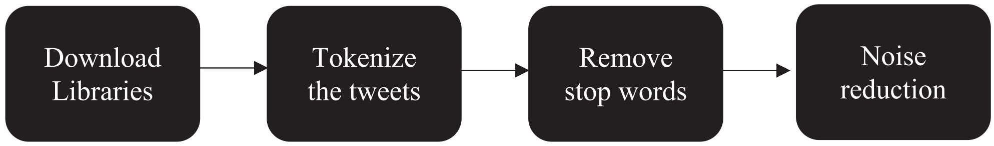


Fig. 2. Data cleansing process.

an exploratory qualitative approach was selected. A structured qualitative survey consisting of open-ended questions was issued to a sample of UK HE employees. The first part of the qualitative survey employed a Critical Incident Technique (CIT) aimed to identify positive and negative experiences with technologies adopted during the first year of the pandemic. The CIT is a well-established methodological tool, used by researchers to capture factual stories and accurate information about situations and events that respondents consider important, by allowing them to describe actual experiences in their own words (Reynolds and Harris, 2005; Stitt-Gohdes et al., 2000). Moreover, critical incidents are easy to remember and can provide accurate information on real events that created either the most negative or the most positive effect on the overall experience (Grove and Fisk, 1997). In our study, respondents were asked to describe any first-hand positive, and then any first-hand negative experiences with technology encountered during the first year of the pandemic. They were also asked to provide as much detail as possible on the specific technologies, why they were adopted and when, and how they were introduced and used during the pandemic.

Following the identification of the positive and negative experiences with technology, and in line with Appraisal Theory, the second phase of the research used a detailed laddering approach to explore, in more depth, how the technologies affected employee emotions and the impact they had on their ability to achieve their goals. The laddering approach has been adopted by several authors to explore different cases of technology adoption, such as wearable technologies (Adapa et al., 2018), use of mobile payments (Sankaran and Chakraborty, 2020), technology resistance (Heinze et al., 2017), and continued use of technology (Ambrose et al., 2020). In our study, respondents were asked laddering questions for each of the reported positive and negative experiences with technology, allowing them to describe in depth the functional and psychological consequences of adopting the reported technologies, following their appraisal of the situation over time. A ‘hard’ laddering approach was employed to collect this information: data were collected using a structured survey. The method was preferred to ‘soft’ laddering (which most commonly utilizes in-depth interviews), because ‘hard’ laddering minimizes interviewer bias and social pressure on respondents, especially around sensitive topics such as emotions (Apostolidis and Brown, 2021; Apostolidis and McLeay, 2016; Grunert and Grunert, 1995). Additionally, hard laddering could be used to collect data from a larger number of respondents, as it is more cost- and time-efficient compared with soft laddering (Henneberg et al., 2009; Russell et al., 2004) and could be used as part of an online survey to enable data collection during the pandemic and lockdown periods. Also, hard laddering has been used in technology adoption studies (e.g., Park et al., 2019).

An example of the qualitative survey questions can be seen in Appendix A. The laddering technique was initiated following the CIT questions which focused on employees' positive and negative experiences with rapid technology adoption during the pandemic. This part of the survey allowed us to answer our first research question on employee perceptions regarding technology adoption in the HE sector. Each respondent used two different ‘free text’ boxes to provide specific and detailed information about the technology reported in their critical incidents descriptions (one for positive and one for negative experiences). These responses formed the basis of the subsequent laddering questions, as respondents were then asked about the functional impact of this technology adoption on their work and the quality of the service they provided. Next, respondents were asked questions related to the emotional impact of these technologies. More specifically, respondents were asked to describe in as much detail as possible, how adopting these technologies made them feel. This enabled us to evaluate the psychological impact of adopting these technologies. Finally, in line with our research objectives, respondents were asked to provide a detailed explanation of any changes in these feelings/emotions during the COVID-19 pandemic period, which allowed us to investigate not only the nature of but also the drivers behind these changes in emotions and perceptions. For every question, respondents were provided with free text boxes to provide information separately for the positive and the negative experiences, and were encouraged to provide details and justifications for all their responses.

By adopting this laddering approach, to focus on the functional and psychological consequences of technology adoption, for the emergency/reactive and for the more planned/proactive stages of technology adoption, respondents were able to move down the ladder of abstraction and provide more in-depth insights into their recent experiences (Grunert and Grunert, 1995). Based on existing studies, we developed and pretested the laddering survey (including a detailed explanation of the process) for our study with a subset of our target respondent group. They had the opportunity to provide comments on the length, comprehensiveness and appropriateness of the online survey prior to its launch. The survey closed by collecting information pertaining to respondents' personal details and their position and level of experience as HE employees.

The survey was uploaded to an online platform and links were distributed through large electronic UK-based HE forums and social media pages, inviting HE employees to participate in a short survey. Over a period of two months, 66 surveys were collected, of which 52 provided useable, in-depth data. All respondents had experience with HE during the pandemic and had reported positive and negative experiences with technology adoption. Thematic analysis and coding were performed in line with the relevant technology adoption and employee emotions literature as summarized in the literature review, to identify the relevant themes relating to technologies adopted, their consequences and any changes respondents perceived during the first year of the pandemic. NVivo 11 software was used to assist data analysis, and identify themes and links between themes.

4. Data analysis and findings

4.1. Step 1 – Social media and sentiment analysis

We began by performing some basic analysis to understand the underlying elements of the data prior to the sentiment analysis. We first ran a frequency distribution on the whole data set, finding 11,736 samples of words, and 173,973 outcomes all included.

The sentiment analysis of our data indicated that perceptions towards technology in the UK HE sector during the pandemic had changed several times during the period March 2020 – February 2021 (see.

Fig. 3). For instance, our sentiment analysis demonstrated that the initial general positive trend in sentiment (March – May 2020) was followed by an extended period of increase in neutral sentiment (June – July 2020). This in turn was followed by a period of rapid increase in negative perceptions towards technology (August 2020 – mid-October 2020). However, this changed in the months that followed (mid-October 2020 – February 2021) when an extended period of almost steady increase in positive perceptions was observed.

To understand better the findings of our sentiment analysis, we developed a word cloud (.

Fig. 4) from social media data, incorporating the top 50 keywords from the full data set.

This step of the analysis demonstrated clearly that technology had been discussed in the context of the COVID-19 pandemic, in relation to the students' experience, the impact on HE and the potential of HE institutions and members of staff to achieve their goals. For instance, it can be seen how the "Virtual" and "International" aspects of "Education" and "Research" are some of the most commonly referenced terms on the areas of HE that have been affected by the introduction of technology. However, it can also be observed that, in addition to the functional consequences of technology adoption, particular focus is also given on the psychological impact, as terms such as "Relief", "Stress" and "Crisis" also have a prominent presence in our word cloud. This finding suggests that, in addition to the nature and quality of the service provided, technology adoption can have both positive and negative impacts on employee psychology and emotions. This also highlights the importance of exploring in more depth, not only the functional consequences, but also the psychological and emotional consequences, to identify factors that may be responsible for the disparity in emotions, and explore whether employee emotions have changed during the pandemic period. Building on the findings of this stage of the analysis we decided that a more in-depth, qualitative investigation of employee perceptions was required to understand better the functional, emotional and psychological consequences that drive these changes in sentiment, and impact on the quality of their work, their wellbeing and their job satisfaction.

4.2. Step 2 – Online qualitative survey

After identifying the changes in sentiment, the second step of our work allowed us to explore in depth the functional and emotional consequences that triggered these changes. In terms of sociodemographic characteristics, our sample was diverse enough to capture the opinions and views of a wide range of people (see Table 1). Respondents ranged in age and gender, with most respondents (approximately 80 %) aged between 25 and 55 years old, while female respondents made up 55.8 % of the sample. More respondents (approximately 55 %) had over 10 years of working experience in HE.

As the analysis of the qualitative data and the classification procedure are largely subjective, two researchers familiar with thematic analysis and the relevant literature coded the incidents independently. Incidents were read and sorted until similar incidents and functional and psychological consequences were assigned to distinct, meaningful categories, and links between themes were clearly drawn. Sorting continued until satisfactory intragroup homogeneity and intergroup heterogeneity were reached, that is, each judge considered that incidents in one category were more similar to each other than incidents in another category. Disagreements between the judges were discussed and resolved mutually.

4.2.1. Types of technology adopted

When analyzing the CIT data, three distinct types of technology were identified more frequently by the participants as having been rapidly adopted by HE institutions in the wake of the COVID-19 pandemic in the UK (and the months that followed), enabling organizations to cope with the challenges caused by the pandemic and the lockdown and social distancing regulations that followed. More specifically, HE employees discussed how universities had introduced:

- Teaching and assessment technologies (such as Blackboard Collaborate, Zoom and digital classroom technologies) to support the students' learning and replace face-to-face sessions;
- Communication and collaboration technologies (such as Skype for Business, Zoom and MS Teams) to enable communication and teamwork between members of staff and/or students. Some of these technologies had also reportedly been used for research purposes, data collection and online (virtual) conferences;

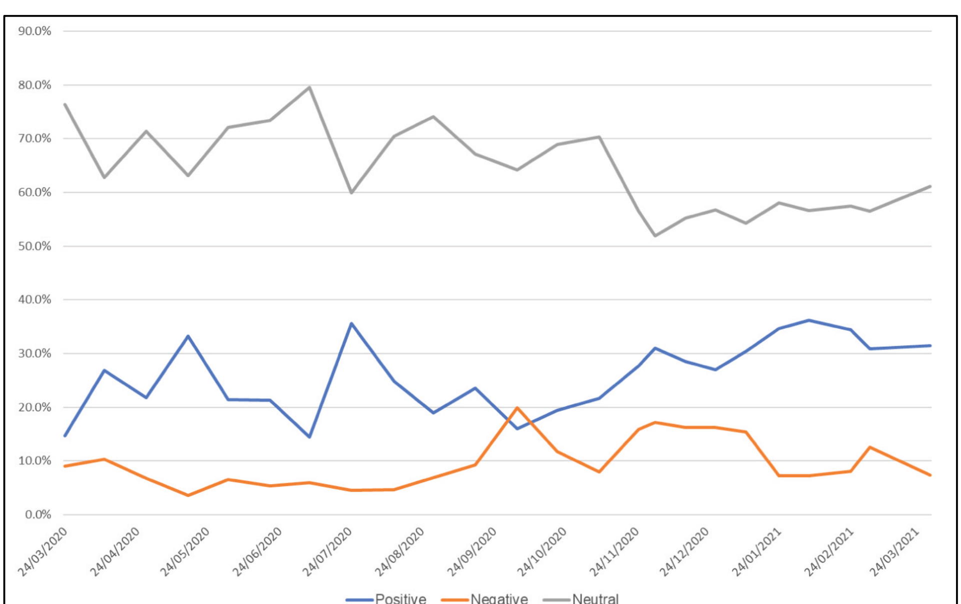


Fig. 3. Sentiment analysis graph.

Fig. 4. Full data word cloud.

Table 1
Sample background information.

	N	Percentage
Gender		
Male	23	44.2 %
Female	29	55.8 %
Age		
18–25	2	4.6 %
26–35	11	21.1 %
36–45	20	38.5 %
46–55	11	21.1 %
56–65	8	15.4 %
Employed in HE		
1–5 years	8	15.7 %
5–10 years	13	25.5 %
Over 10 years	20	58.8 %

- File storage, sharing and management (Moodle, Dropbox, OneDrive) to enable management and sharing of documents and information among members of staff and/or students.

Both positive and negative experiences were discussed as critical incidents regarding both the emergency (rapid) and the more proactive (planned) adoption of these technologies, and were explained further in the laddering stages of the survey. Interestingly, information from our respondents corroborated the findings of the sentiment analysis as it suggested that the emotional consequences of technology adoption changed over time, which supported the changes between periods identified in the sentiment analysis. For example, according to our participants:

> It has been an emotional rollercoaster, initial uncertainty and stress was replaced by eagerness once we became more confident with the new technologies, until the university decided to change the way they do things and use a different approach to online delivery and assessment – claiming it was for consistency and to improve the student experience, although all they were trying was to save money. After spending all the time and effort in learning how to do things one way, we had to go back to square one and redesign our modules and assessments. […] Now at least we know which system we have to use, so I guess I feel better about that, but it's upsetting when you have to do everything twice. [Respondent 16].

As such, the findings of this stage of the research will be presented by phase as identified in the sentiment analysis (see Section 4.1) and discussed by our respondents.

4.3. Four phases of technology adoption

4.3.1. First phase (Secure)

During the first months of the pandemic, respondents reported that the rapid adoption of the aforementioned technologies had several positive functional consequences as it helped them safely perform their daily tasks and achieve their short-term goals. More specifically, respondents associated rapid technology adoption with the ability to perform their work activities (such as teaching, research and meetings) without compromising their health and safety. Additionally, improvements in efficiency due to technology adoption were reported since the early stages of this period; respondents argued that technology adoption allowed them to save time, work on multiple tasks and organize and attend events and sessions online, which provided them with an efficient and secure way to collaborate and connect with others. For instance, respondents argued:

> Personally, I did not find it a difficult transition and find lots of elements of working remotely very useful for the type of work that I do. [Respondent 31].

> Online teaching was not perfect, but at least allowed those of us with health conditions to safely teach our students […] Definitely better than the alternative – having to catch the bus to Uni with dozens of people not wearing masks, sit in an office with 4–5 other people and teach in lecture theatres of 150–200 students during a pandemic. [Respondent 23].

In addition to the improvements in efficiency and health and safety, respondents explained how this rapid adoption of technology resulted in a steep learning curve that enabled employees to improve their technological skills and confidence quickly, which they considered an additional functional benefit:

> A massive and all-round improvement in relevant skills – for staff and students, born out of necessity and key in terms of employability for students and for delivery of our learning and teaching strategy for staff. [Respondent 8].

Using the laddering approach, respondents were able to link these functional consequences to psychological/emotional consequences. Specifically, respondents were able to link the positive functional consequences of improved efficiency, skills development and safe working conditions to feelings of *empowerment*, *security*, *excitement* and *accomplishment* related to adopting new technologies and developing new skills. According to our participants, this positive psychological impact also affected their overall performance and wellbeing and improved their engagement with the new technologies:

> I think I was one of those people that were actually happy with moving all our meetings to online. I felt safer working from home during the pandemic and I was actually quite happy not having to commute one and a half hours every day, and I was able to do so much more in a working day, so I was quite relieved when the email came through that we are going fully online – both times. [Respondent 27].

> I was excited at first. Having the opportunity to work some days from home was ideal for me and helped me focus more on my research. [Respondent 51].

On the other hand, the rapid technology adoption also had several negative functional consequences which affected the employees. Respondents reported extensively on how this rapid adoption of unfamiliar technologies created challenges for employees and resulted in additional requirements for employee time and effort (e.g., for training, preparation or familiarizing themselves with the new technologies) as not everyone had the required knowledge or experience. Similarly, issues relating to limited access to equipment and software that would allow employees to use the adopted technologies were reported as an outcome of rapid technology adoption:

> I think a lot of colleagues found the move to meetings being online problematic and a number of individuals had issues with Zoom. [Respondent 6].

> It also took the University some time to furnish me with the requisite tech to do my job (laptop, 2nd monitor, keyboard/mouse, ergonomic chair), so this meant I had to use my own computer and equipment for a while and this has resulted in me suffering with exacerbated musculoskeletal issues. [Respondent 11].

Additionally, the use of technologies to replace personal interactions initially had a negative impact on the quality of communication, while the efforts to compensate for the lack of physical contact by introducing several different channels of communication resulted in channel/platform fragmentation, which in turn led to confusion, loss of productivity and additional work for the employees:

> We realised that the sudden increase in student emails was because the School has asked staff members to use so many different channels to communicate with our students to compensate for the lack of face-to-face interactions, that pieces of information were shared on many different channels. This led to confusion and students have given up on looking for all this information in different places and they were emailing their questions to their tutors instead. [Respondent 44].

> We have used multiple platforms at times and this can be confusing. Teaching online requires a different approach and it can be sometimes more difficult to engage students. […] Although in some cases it saved some time (e.g. from commuting), not being able to interact personally with students and colleagues had an adverse impact on the quality of the service. […] Students had more questions that were going unanswered and creating too many new channels of communication further confused students and increased the time and effort required from staff to create and maintain that channel of communication that introducing new platforms actually had a negative effect on student and staff satisfaction. [Respondent 52].

These negative functional consequences of technology adoption during the first period affected employee psychology and emotions. Respondents argued that the rapid adoption of unfamiliar technology, the lack of personal interaction and the communication fragmentation, as well as the additional work (in terms of time and effort) led to feelings of *fear of use of technology*, *frustration*, *apprehension* and *stress*. For example:

> Initially I was very nervous of using the technologies and feared mostly about the loss of personal contact with my peers and staff members. But I think everyone had this fear. I also was not very technology confident, so I had to learn very quickly as we were under pressure to deliver a major project when COVID-19 struck. [Respondent 9].

> Deciding to move to recorded student presentations (instead of face-to-face presentations) as part of the assessment. This decision was taken as a way to minimize the impact of COVID on the student experience. Unfortunately, recording team presentations has proven to be very challenging and stressful both for students and staff and had a negative impact on student satisfaction and their overall learning experience. It also meant that members of staff had to put in a lot of additional work to make sure they answer all student questions on time and resolve any issues. [Respondent 50].

4.3.2. Second phase (Scrutinize)

Differentiating from the first phase, HE employees discussed a second phase of technology adoption, when they reportedly had the opportunity to reflect on the technology introduced during the first period, and identify strengths and areas for improvement as they were planning their future activities. The adoption of different technologies during this reflection and planning stage provided people with the opportunity to try and test different tools, platforms and approaches in a less stressful environment (compared to the first phase) and identify ways to improve their performance in the 'new normal'. Furthermore, the technology adopted facilitated group discussions and sharing information regarding the use of technology, best practice, and things to avoid based on expert advice and peer employee experiences over the previous months, supporting feelings of *confidence* and *self-efficacy*:

> After the initial weeks of panic, I had the time to look into the different software we had access to and try a few things […] I am not very tech savvy, so wasn't always successful, but I had a few Zoom meetings with people that had used them before and they were able to walk me through setting them up for my own courses […] so didn't feel completely useless. [Respondent 21].

On the other hand, during this second phase of technology adoption the first issues relating to employees' resistance to engaging with the new technologies were reported, as respondents described employees' feelings of *frustration*, *isolation* and *fatigue* due to the additional workload, continuous use of technology, lack of physical contact and multitasking. In addition to the impact of technology on their own feelings of fatigue and isolation, respondents reported a general employee resistance and lack of engagement with technology during this period, which made collaboration and communication even more challenging, and further worsened the negative psychological impact of technology adoption in this phase:

> Continuously being in front of a screen is not healthy for long periods of time. Screen fatigue, eye strain and headaches and also not moving

about enough, insufficient breaks, can also impact negatively on posture. Can feel isolated. [Respondent 44].

One negative I would see would be the lack of engagement from some staff members. This has resulted in others having to pick up the slack. When in the office and face to face it is easier to discuss and determine the reason why work is not completed on time or at all. […] So from that perspective some elements of work were not effective. [Respondent 9].

As can be observed from the above quotes, the lack of employee engagement had a negative impact on employee psychology as they reported feelings of *frustration*, *isolation*, *helplessness* and *fatigue*.

4.3.3. Third phase (Streamline)

Following the reflection phase of technology adoption, respondents clearly discussed a separate phase where technology adoption had a distinct impact on employee emotions. Respondents argued that adopting the technology became less of an emergency and more planned in the period following the first few months of the pandemic, there was an increasing attempt by universities to streamline the use of technology and strategically incorporate specific technologies to support their activities; moreover, to improve the learning experience and satisfy (e.g., through different synchronous and asynchronous channels) the large group of students not fully satisfied with their experiences with the technology adopted thus far. From a functional perspective this more strategic adoption of technology meant less ambiguity and uncertainty. Additionally, in many cases this meant adoption of technologies that employees were familiar and confident with, and had access to the required equipment, training and support, which improved their perceived efficiency, reduced uncertainty and stress and had resulted in strong feelings of *empowerment*, *confidence* and *relief*:

Having our teaching and meetings online helped me get some peace of mind […] The more we used online software the more I realised how much easier it is to finish certain things when working online. […] Collaborating with others is a lot easier online. [Respondent 4].

Sigh of relief really […] At least all my efforts of finding how to set up my teaching online did not go to waste. [Respondent 14].

Interestingly, however, efforts towards a more strategic adoption of technology in this phase also created several challenges as they had a substantial negative effect on functional and psychological consequences. Specifically, several respondents reported how the efforts of the HE institutions to streamline, organize and make consistent the use of technology involved in their processes, and their efforts to satisfy the students and the lack of personal interaction, meant additional use of technology but also less flexibility in their technology (in terms of the nature and the extent of the adopted technology). This led to the reported adoption of suboptimal technologies that limited the employees' potential to achieve their objectives and also respond to changes in the environment (pandemic waves, regulations, technology failures). This lack of control increased *frustration* and feelings of *helplessness* for many employees. Furthermore, the additional technology adoption to support work activities at this stage prolonged the continuous use of technology and lack of personal interaction which further amplified feelings of *isolati*on and *fatigue*:

As time went on, students missed the social aspects of learning and being on campus and we, in response, increased the number and format of synchronous activity but ensuring that ILOs [Intended Learning Outcomes] could still be achieved via asynchronous learning for those less able to engage with the synchronous. [Respondent 6].

Also the recent efforts of the University to micro-manage what technology we should use and how, regardless of the nature of the module or the kind of relationship and rapport we want to establish with students feels very limiting. Students and myself were feeling very comfortable using Zoom for our seminars, but we were asked to change to a different platform, which is not as good for the purposes of our workshops. [Respondent 17].

4.3.4. Fourth phase (Sustain)

Following the first three phases of technology adoption, respondents discussed the impact of technology during the final few months of the first year of the pandemic. A more positive impression was communicated as employees reportedly familiarized themselves further with the technologies and the new ways of performing their tasks, and improved their skills and confidence. In this fourth phase, respondents recognized the flexibility and the improved efficiency that technology adoption could allow in certain aspects of their job:

For me, the most positive aspects of this technology adoption are Team meetings and the flexibility to adopt new ways of working and rethink old ways of doing things. I find the most positive change has been shorter and more action focussed meetings. […] I still enjoy the flexibility of working from home and adopting new technologies however I am missing the social interaction now and look forward to seeing colleagues face to face. The main feeling that has changed is that working from home feels normal and so it will be a change now to transition back to being on campus and hybrid working. [Respondent 31].

I'm very easy with a lot of the technology now and glad that we will continue to have some webinars to ensure access for all students. Also our lectures are all to be recorded which is great. Face-to-face teaching will be all workshop and seminar stuff. This is great, we have been questioning the value of traditional lectures for years but it took a pandemic to kill them off! I really like having office hours online. Student attendance is much better if they can call you from wherever they are. [Respondent 12].

Staff capacity for using technology in their learning and teaching has improved dramatically and, like everywhere, at a much faster pace than would have been possible otherwise. Anecdotal evidence suggests that many staff will embrace a more blended delivery model as we exit COVID-19 and as per the School's Learning and Teaching Strategy, but whether this transpires remains to be seen. [Respondent 6].

Flexibility and increased efficiency were associated with positive psychological consequences, mainly feelings of *happiness*, *self-efficacy* and *empowerment*. Therefore, respondents identified the aspects of the adopted technology they were willing to maintain in the longer term, in the 'new normal' following the pandemic.

Conversely, respondents also recognized that technology adoption in the long term needs to take into consideration the negative functional and psychological consequences, mainly relating to feelings of *isolation*, *stress* and *fatigue* (due to the over-use of technology and the additional workload created as a result of technology adoption). Finally, feelings of *fear* were also reported as a negative emotional consequence of technology adoption in this phase. Nevertheless, unlike the reported feelings of fear and stress of technology adoption in the previous phases, in this period the fear was related less with the use of new and unfamiliar technologies and more in terms of technology/network failure, as most activities relied heavily on those.

I think initially most of the stress came from the uncertainty due to the unfamiliar software/platforms/technology. Later on as the technologies were implemented and used there was more fear about technology or network failure. Stress levels decreased overall but any initial excitement for the adoption of new technology was quickly transformed to tiredness and exhaustion from having to engage with so many new technologies. [Respondent 52].

> I do still worry about the lack of personal contact and feel that it is hard to continue to be engaged online all day every week. It is exhausting and workload has increased as a result of COVID. [Respondent 8].

> Whilst I do miss face-to-face contact with colleagues, from a well-being perspective, I would prefer a blended approach going forward. Screen fatigue is real though! [Respondent 10].

4.4. Enablers of positive and negative emotional consequences

A further interesting finding from our qualitative data analysis was that the nature of emotions (e.g. positive or negative) could change during these phases, even for the same employee. This meant that emotions were not stable, and employees appraised the impact of technology on their potential to achieve their goals (primary appraisal) and their control over the situation (secondary appraisal) differently throughout the first year of the pandemic, which had an impact on their feelings and emotions. For example, initial excitement for technology adoption was replaced by stress and fear of technology failure, particularly in cases where respondents had limited control, and later by fatigue and feelings of isolation and helplessness, as the following example demonstrates:

> I remember clearly how excited I was when we were told that we could teach and meet online […] I felt that working from home was safer and I could accomplish more […] It [technology] has not always been reliable which resulted in a lot of double doing, working over weekends and making sure that contingencies are in place […] Now I am happy when I get to go to the office and see other people. [Respondent 18].

In relation to the impact of technology adoption during these four phases, as well as the interphase changes in emotions, respondents acknowledged the importance of effective training and support, access to required equipment, and flexibility and control over the adopted technologies. Additionally, participants reported how technology adoption became more effective (and they felt more positive about it) when in addition to introducing new technologies, the processes and activities of the HE institutions changed to reflect the changes from the pre-pandemic situation. For example, respondents explained how sufficient and timely (official and unofficial/peer) support and guidance improved employees' technological skills and confidence, and had limited the negative psychological impact and facilitated positive emotions:

> I would say that the most positive experience throughout the pandemic was with using MS Teams for staff and student meetings. Although people were allowed to use different platforms if they wanted to, from the very beginning we were encouraged to use MS Teams to organize meetings with students, and we consistently used MS Teams for departmental/RC [Research Centre] meetings. We were offered training on how to create teams, share files etc. and this ended up saving us a lot of time, money and effort. [Respondent 6].

Furthermore, effective communication between employees and HE institutions was considered key in limiting the negative functional and psychological impact of technology adoption and improving employee perceptions and attitudes towards technology. For example:

> The attitude of the university towards the staff was condescending and from a few managers borderline bullying. I think this was probably caused by the nervousness of senior management in the face of very hard decisions. I found it dispiriting and my trust in the university's management has not recovered. [Respondent 13].

5. Discussion

Contributing to existing literature on technology adoption, the current study explored the emotional and psychological impact of (rapid) technology adoption on HE employees, using the UK HE sector in the first year of the COVID-19 pandemic as a context where the introduction of technology was initially rapid and reactive (Hofer et al., 2021). This was particularly interesting as, unlike other studies that have examined technology adoption, it allowed us to explore the transition from the emergency/rapid adoption of technology in early 2020 to the more planned and carefully designed adoption in the months that followed, and the changes in employee emotions during this process (Rapanta et al., 2021).

By employing a sentiment analysis of social media content (tweets), supported by a collection of primary qualitative data using the CIT and laddering techniques, our study was able to identify not only the changes in sentiment and perceptions towards technology in HE, but also explore in depth the nature of these emotions and the triggers behind any changes. First, our social media (Twitter) data analysis offered some very useful insights into one of the most controversial topics in the HE industry during the pandemic, as it allowed us to explore perceptions towards technology adoption during the first year of COVID-19 in the UK. The sentiment analysis clearly indicated that feelings and perceptions towards technology adoption changed during the time frame of our research. A closer look at the social media information suggested that in addition to the much-debated impact on the nature of the HE service and students' engagement, learning experience and academic performance (e.g., Camilleri and Camilleri, 2021; Iglesias-Pradas et al., 2021; Rapanta et al., 2021), the impact of technology adoption on employee emotions and feelings was also evident. Our wordcount analysis of the social media information highlighted the links between technology adoption and a number of different emotions, which further highlighted the importance of exploring this aspect of (rapid) technology adoption, as emotions could affect employee satisfaction, wellbeing, performance and quality of work (e.g., Cho et al., 2017; Moreo et al., 2020).

Building on the findings of the sentiment analysis, the current study adopted Appraisal Theory (Lazarus, 1991) as a lens to explore the impact of technology adoption over a period of 12 months. Unlike previous studies, Appraisal Theory allowed us to explore this impact over a longer period of time. By adopting the Appraisal Theory lens, an online qualitative survey was developed utilizing the CIT and laddering techniques, which allowed us to explore the primary and secondary appraisals of employees during the rapid/mandatory – and then the more planned and strategic – periods of technology adoption. The findings of our CIT and laddering qualitative data analysis suggest the existence of four phases in technology adoption and the transition from emergency to planned technology adoption, which reflect and explain the changes in sentiment during this period.

The first phase covered rapid technology adoption and was defined by a diversity of feelings. The employee appraisal of technology adoption in this phase resulted in a positive evaluation of the situation. The most commonly reported positive feelings and emotions included empowerment, security, excitement and accomplishment as employees acknowledged the improvements in efficiency and safety, as well as their own skills and knowledge that technology adoption offered at this stage. This corroborates the arguments by Lee et al. (2011) who suggest that technology adoption can lead to feelings of pleasure and arousal.

Interestingly, our findings in this first phase also support the technology adoption paradox first identified by Mick and Fournier (1998), as although positive functional and psychological consequences are attributed to the adoption of emergence technology, several negative appraisals of the situation are also reported. More specifically, corroborating findings from earlier studies (Kay and Loverock, 2008; Pozón-López et al., 2021; Wood and Moreau, 2006) relating to emotions during the early stages of technology adoption, emotions such as fear of use of technology, frustration, apprehension and stress, are associated with the rapid adoption of unfamiliar technologies. In many cases, this is supported by a secondary appraisal of the situation. Although the necessity of technology is recognized by the employees, the unfamiliar technology and limitations in training and access to support and equipment during this phase negatively affected feelings of control and coping with the situation which resulted in negative emotions. As such we named this first phase '*Secure*', given the links between technology adoption and health and safety, and securing the institutions' operations.

Following the first phase, our qualitative data findings indicated a second more 'reflective' phase, as technology adoption moved from 'rapid' to 'planned' and the use of technology enabled people to try and test different tools and communicate and share solutions, best practices, and challenges. In many cases, this reportedly improved control over a negative situation (secondary appraisal) and led to positive feelings of confidence and self-efficacy. Nevertheless, in this case the first signs of feelings of technology fatigue, isolation and helplessness were reported, as employees negatively appraised the extensive use of many different technologies to replace face-to-face interactions. This is in line with arguments of previous authors who suggest that fatigue (due to the increased use of technology), social isolation and loss of control can be some of the negative outcomes that individuals may attribute to the extensive adoption and use of technology (Lee et al., 2003; Meuter et al., 2003; Mick and Fournier, 1998; Ratchford and Barnhart, 2012; Thompson et al., 2005). In our sentiment analysis, this reflection phase seemed to coincide with a drop in the positive sentiment being replaced by an increase in the neutral sentiment, which could support our arguments. Therefore, we have given this phase the title 'Scrutinize'.

The third phase of technology adoption discussed by respondents in our qualitative survey clearly discussed a move towards a more strategic adoption of technology by HE institutions and employees. During this phase, the reported limited control of employees over the technology adopted and how it would be used resulted in feelings of frustration and helplessness, indicating a negative secondary appraisal. On a primary appraisal level, the prolonged period of technology use was considered as impeding the achievement of employee goals, and increased feelings of fatigue and isolation. This resulted in several cases of technology resistance from employees as they reportedly refused to engage with the technologies adopted by the institution, which made collaboration and communication even more challenging. This supports arguments by earlier scholars who purport that new technologies are often met with resistance by employees, which can affect negatively the use of technology and the organization processes (Smart and Desouza, 2007; Zheng and Montargot, 2021). This further highlights the importance of exploring the impact of technology on employee emotions (Zheng and Montargot, 2021). This was also evident in the sentiment analysis as there was a clear and consistent drop in positive sentiment. This time, however, it was followed by a strong increase in negative sentiment during the same period. As has been discussed, one of the main challenges faced in this phase of technology adoption was the attempt of organizations to streamline their strategies, which in many cases resulted in loss of control and employee resistance; thus we have identified this phase 'Streamline'.

The final phase discussed by participants followed the attempts for more strategic introduction and adoption of technology than in the previous phase. In this context, participants discussed how in addition to technology adoption, several institutions had adapted their processes and management to fit this new normal, creating a more conducive environment for effective integration of technology. This strategic adoption of technology was positively appraised by employees and resulted in feelings of happiness, empowerment and self-efficacy, which can positively influence adoption and acceptance of technology (Lee et al., 2003). This was supported by the sentiment analysis and the clear increase in positive sentiment which was evident in the last few months of our data period. Furthermore, having appraised their experiences with technology in the previous phases, in the fourth phase participants identified specific favoured technologies and/or tools they would adopt in the longer term, considering them beneficial to help them achieve their goals. Simultaneously, participants were also able to critically evaluate the adoption of technologies in the long term, supporting the amplified negative effect that any failures in technology would have, as well as the increased fatigue due to long-term use of technology. As participants discussed technology adoption in this phase, and its benefits and challenges in the longer term, we have titled this phase 'Sustain'.

By combining the findings of the sentiment analysis and the thematic analysis of our qualitative survey data, Fig. 5 presents the different phases in technology adoption identified in our discussion. While in Fig. 5 we utilize the X axis combined with dashed lines to represent the date at which the phases 'change', we recognize that these are not fixed points in time. Given the nature of our qualitative work, we are using this graph to highlight the emergent phases on the continuum of time. The dashed nature of the line means that we recognize that the time for each phase (and overall) is fluid, and may be different depending upon the HE institution, country, or the broader situation in which (rapid) technology is occurring.

In addition to identifying the four phases based on employee emotions following the appraisal of technology adoption and use, our findings allowed us to examine the factors that could influence secondary appraisals. That is, a closer investigation of our CIT and laddering data allowed us to identify the factors that may strengthen or challenge perceived coping and control of a negative experience with technology adoption. More specifically, our participants highlighted that sufficient and timely training and support, adjustment of organizational processes to reflect the 'new normal' in HE, access to required equipment and meaningful two-way communication with the organization could increase perceived control over a negative situation. Additionally, empathy from the organization could improve perceived ability to cope with the situation. Therefore, we called these factors enablers, as they could support positive secondary appraisals even in the case of goal-incongruent (negative) events by improving employee control and coping. Fig. 6 summarizes the findings of our study.

6. Conclusions

Given the important role of emotions in technology adoption, employee satisfaction and performance, the current study contributes to the existing literature by exploring the impact of technology adoption on employee emotions in HE as technology adoption moved from emergency (rapid) to planned (designed) during the COVID-19 pandemic. To achieve this, a two-step methodological approach was employed to: a) explore sentiment and any changes in perceptions towards technology adoption during the first 12 months of the pandemic; and b) identify the functional and emotional consequences of technology adoption that influence these perceptions. The findings of our analysis identified four phases of technology adoption during this period, each one with distinct characteristics in terms of the impact of adoption on employee emotions. Additionally, our study identified the factors that can support more positive emotions by improving control and employee coping.

Our findings contribute to existing academic literature in many different ways. First, our study focuses on the under-researched area of the psychological and emotional impact of technology adoption. Although earlier studies have investigated the role of certain emotions (e.g., fear, stress, excitement, hype) in relation to technology adoption, to date very little information has been shared about the impact of technology adoption on employee emotion. As previous studies have emphasized the importance of employee emotions for organizational performance, job satisfaction, employee commitment and turnover intentions, we believe that our paper makes a strong contribution to existing knowledge in this area.

Furthermore, by exploring the period from the initial emergency technology adoption to the later more planned stages, our research demonstrates how emotions and feelings can change during this process.

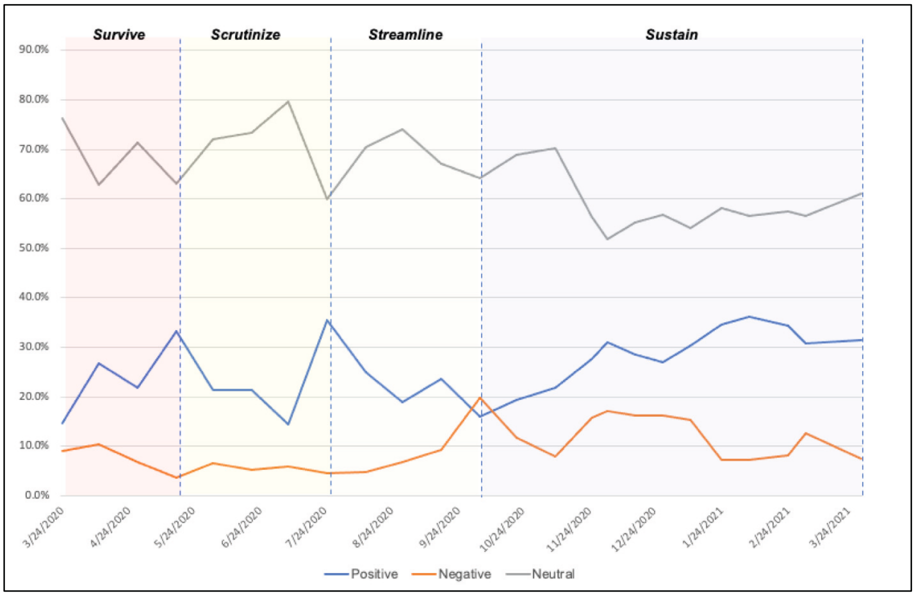


Fig. 5. Sentiment analysis and the four phases of adoption.

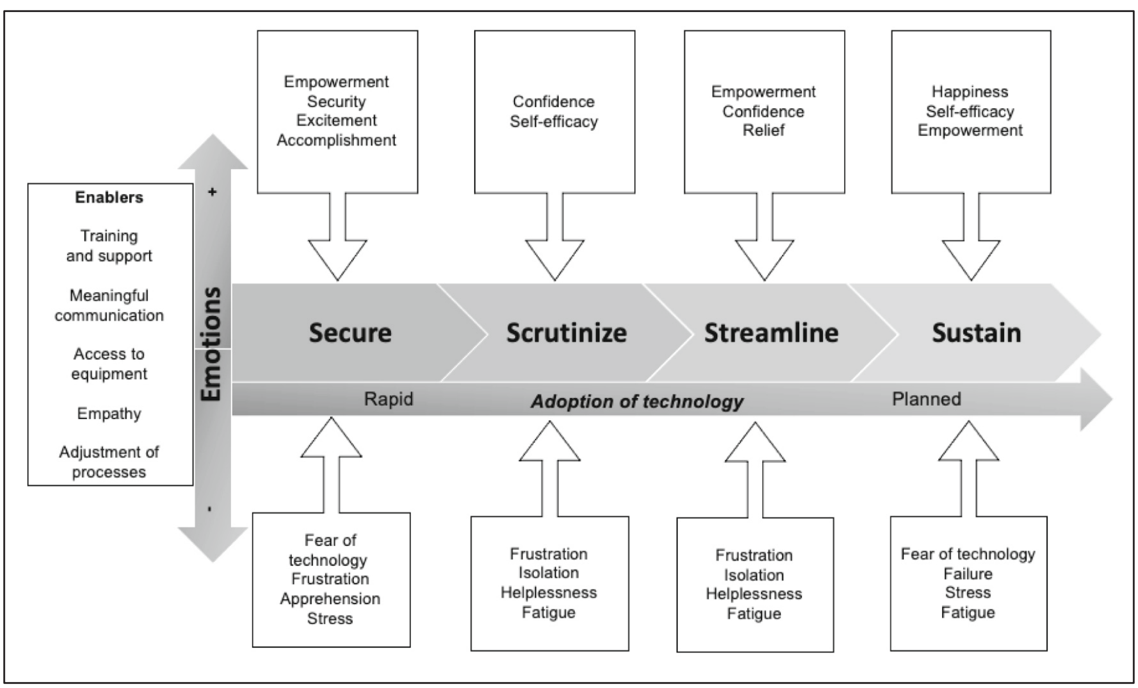


Fig. 6. Impact of technology adoption on employee emotions.

To the best of our knowledge, this is the first study that investigates the changes in psychological and emotional consequences during the transition between emergency and planned technology adoption. As emergency technology adoption is an increasingly common phenomenon in organizations, due to the pandemic but also other external and internal factors (e.g., development of disruptive technologies, increasing competition), it has attracted growing interest from academics, practitioners and policymakers. Thus, we believe that our findings make a valuable theoretical contribution as they provide a new 'lens' based on Appraisal Theory, that can be used to explain the psychological impact of technology adoption as a multi-stage phenomenon, contributing to a very topical area of research.

Finally, by developing a framework that defines the different phases from emergency to planned technology adoption based on employee emotions as well as the factors that can enable (or impede) positive psychological consequences, we create a strong link between the psychology, technology adoption and business management research areas that offer several opportunities for further academic research.

6.1. Managerial and practical implications

By providing a better understanding of the emotions involved in the different phases of technology adoption, our findings can support businesses that must deal with the challenges of emergency technology adoption and help them make the transition to planned adoption more easily. The identification of the four phases of this process and the emotional and psychological consequences, although derived from employees in the HE sector, are also applicable in other contexts where emergency technology may be adopted. Our findings suggest that by identifying effective ways of supporting the transition to a more strategic integration of technology, managers can encourage use of technology, reduce employee resistance, support business processes, and improve employee satisfaction and wellbeing. Additionally, by using our qualitative data to identify several enablers of positive emotions, we argue that our findings can inform practitioners how to strategically manage technology adoption to avoid negative emotions that may affect employee satisfaction and performance. For instance, by offering empathy and meaningful communication, managers can reduce employee resistance to technology adoption, while adjusting the processes to support more meaningful integration of technologies can reduce negative emotions and support feelings of empowerment and self-efficacy.

6.2. Limitations and further research

As with all research, this study also has certain limitations. First, although Twitter was chosen due to its popularity in academic and HE professional circles, it must be acknowledged that there are other social media platforms that could be used by HE employees to express their opinions and perceptions about technology adoption. Although the preference of academics and professionals to use Twitter to disseminate information and opinions, due to its broadcasting nature, has been acknowledged by researchers, its more restrictive nature (maximum 280 characters per tweet) compared to other social media platforms may mean that sentiment analysis may be less impactful. Nevertheless, the number of tweets that we were able to retrieve from the Twitter platform (almost 9000 tweets), means that Twitter remains one of the dominant platforms for people in HE.

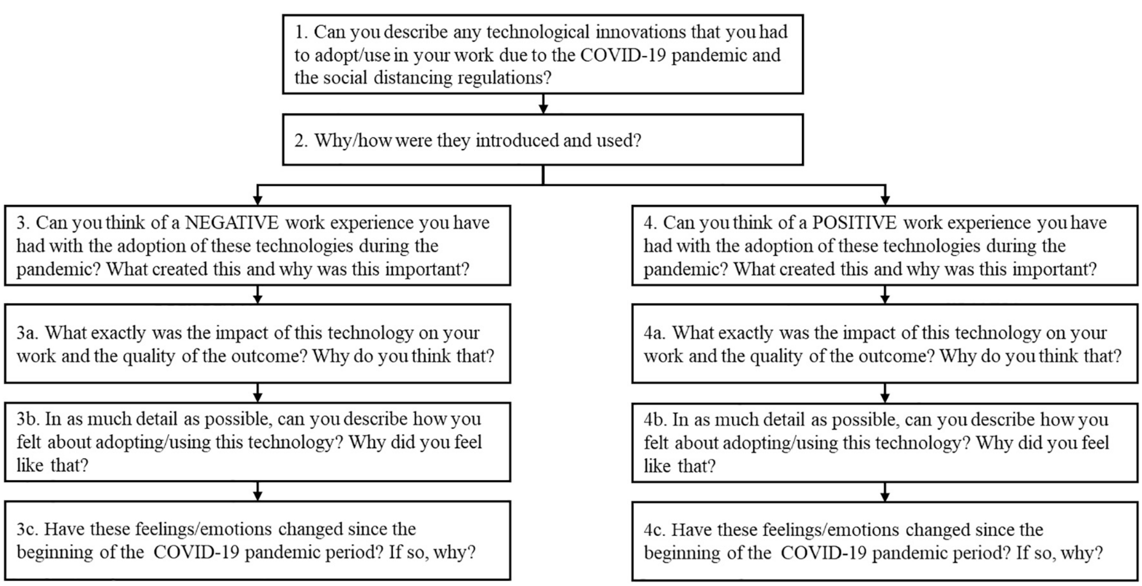
We also argue that another limitation in this paper is our current use of sentiment analysis. We have mainly focused on using sentiment analysis and text mining to analyse the Twitter data. While this is appropriate and rigorous, there is an argument that the data could be analysed with a different sentiment perspective. In the current approach the focus is on emotion detection, looking at positive, neutral and negative tweets. A further step is to develop this approach in more detail and consider aspect-based sentiment analysis. In such a scenario researchers would break down the tweets even further, allowing for the analysis of each tweet and its key aspects, which are mentioned in a positive, neutral and negative manner. By focusing on the aspects of the tweet in correlation with our text-mining approach there is the possibility of creating advanced analysis which could gather tweet sentiment but also specific aspects of the tweet, providing a richer analysis of the data.

A further limitation surrounds our choice of using an online qualitative survey that adopted CIT and laddering techniques. Although this allowed us to explore in depth the impact of technology adoption using information from a range of HE employees, the overall number of respondents (52) relative to the total number of UK HE employees provides opportunities for researchers to expand our qualitative sample. Further, this area of research would also benefit from studies that employ quantitative methods which can build on the in-depth findings of this study, to capture the opinions and perceptions of more employees to validate our findings. Finally, although our research focused on the adoption of technology by HE employees, future studies could include different stakeholders, such as students, as this would allow investigation into how technology adoption affects both employee and student emotions and influences student satisfaction and the student learning experience.

Data availability

Data will be made available on request.

Appendix A. Qualitative survey questions



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