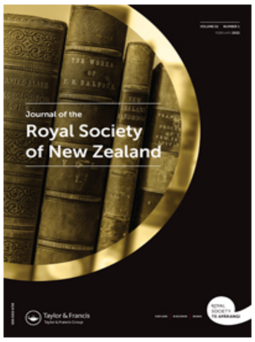

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RESEARCH ARTICLE

Partnering with AI: the case of digital productivity assistants

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ABSTRACT

An emerging class of intelligent tools that we term Digital Productivity Assistants (DPAs) is designed to help workers improve their productivity and keep their work-life balance in check. Using personalised work-based analytics it raises awareness of individual collaboration behaviour and suggests improvements to work practices. The purpose of this study is to contribute to a better understanding of the role of personalised work-based analytics in the context of (improving) individual productivity and work-life balance. We present an interpretive case study based on interviews with 28 workers who face high job demands and job variety and our own observations. Our study contributes to the still ongoing sensemaking of AI, by illustrating how DPAs can co-regulate human work through technology affordances. In addition to investigating these opportunities of partnering with AI, we study the perceived barriers that impede DPAs' potential benefits as partners. These include perceived accuracy, transparency, feedback, and configurability, as well as misalignment between the DPA's categorisations of work behaviour and the categorisations used by workers in their jobs.

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Introduction

Artificial intelligence (AI) is forecast to play a key role in transforming the future of work (Faraj et al. 2018; Strich et al. 2021). It has been suggested that AI-based information systems should be seen as partners rather than tools for work, due to their advanced capabilities such as machine learning and natural language processing (Kravchenko and Kyzymenko 2019) and that a reciprocal relationship is needed for human-AI collaboration to meet its potential (Schuetz and Venkatesh 2020). Field-based research in this area is emergent and important, given that there are known challenges to partnering with AI. Today's machine learning technologies have increasing levels of autonomy and capacity for learning but are also known for their inscrutability (Baird and Maruping 2021; Berente et al. 2021). They can limit human-AI interaction and lack the ability to convey how they reach decisions (Strich et al. 2021). Further, it has been suggested that particular human capabilities or competencies are needed to work with AI (Lewis and Clutterbuck 2019). Understanding the human-AI relationship as it occurs in practice is, therefore, an important area for research.

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In more recent times, there has been a focus on personal work analytics, with some early studies showing the potential to improve workers' productivity and wellbeing (e.g. You et al. 2021) by capturing data on their behaviour and making suggestions on how they can improve. However, as noted earlier, an understanding of the human-AI relationship as it occurs in practice is currently lacking, which prevents researchers and practitioners from addressing negative attitudes and resistance when AI is introduced to help workers (Chiu et al. 2021).

We aim to help address this gap by investigating human-AI interaction in an emerging context – productivity and wellbeing at work. We conduct an interpretive case study (Walsham 1995) examining the deployment of an enterprise-level Digital Productivity Assistant (DPA). Our overarching aim is to understand the emergent role of such tools vis-a-vis their human partners, i.e. how AI can help workers to improve their productivity and wellbeing in the workplace. We consider the following research questions:

- What opportunities do AI-based assistants offer when it comes to improving individual workers' productivity and wellbeing in the workplace?
- What are the barriers experienced by workers to using AI to improve their productivity and wellbeing?

The paper is structured as follows. In the Background section, we explore related studies in the area of productivity and wellbeing in digital work, discuss the concept of a Digital Productivity Assistant (DPA), and the theoretical lens of co-regulatory theory and technological affordances. We then explain our methodological approach to data collection and analysis. This is followed by our findings on the DPA's contributions to improving individual workers' productivity and wellbeing in the workplace and the barriers experienced by workers when using the AI. Next, we provide a discussion about how our findings apply more broadly to other settings, focusing on three main areas: accuracy, transparency, and feedbackand then finish with a conclusion and outlook.

Background

Productivity and wellbeing in the context of digital work

There is a range of related work on productivity and wellbeing in the context of digital work across a number of disciplines. Cho and Voida (2020) argue that most of the work in HCI and CSCW on productivity and wellbeing has assumed that work is conducted in an office setting. They note that post-COVID there will be significantly more work from home, and that consequently, more attention needs to be given to supporting productivity and wellbeing when work is done at home, which differs from the work context in a number of ways, such as the presence of family members, and differing time demands. They argue for a more flexible consideration of time, and a more holistic view of productivity that does not focus so much on narrow metrics such as tasks completed, which reinforces the idea that being busy is good, rather than promoting a more result-oriented view. Kim et al. (2019) identify six themes that affect whether an activity is seen as productive. These include not just the more obvious ones (such as producing work products, where factors include the quality, quantity, and nature of the product), but also time management aspects (efficiency of time use, the intensity of focus, and whether tasks were completed on time [‘punctuality’]), as well as mental and emotional states (e.g. attention vs. distraction), and the impact and benefit of the task being performed. They, therefore, argue that productivity tracking tools tend to measure what is easy to measure and that the notion of productivity used is too simple and too narrow. Our findings are consistent. In particular, we highlight that Microsoft MyAnalytics’ conceptualisation of categories of time use is too simplistic (focus time vs. meeting, with the aim of minimising the latter). Kim et al. document a range of task categories, for example, the task of Learning, which is seen as productive, uses both individual activities (focus time) and meeting-type activities (e.g. attending seminars). Similarly, the task of Communication could be done using face-to-face meetings, conference calls, or email. Additionally, especially important when considering wellbeing, Kim et al found that participants included non-work-related tasks that were considered productive, such as health, leisure activities (both individual such as watching Netflix and group such as a team retreat), social activities, and living (e.g. shopping and housework). Kim et al also flagged ‘the need and opportunity for customising productivity trackers to fit an individual’s context and preference’ (p.10).

Wajcman (2019) considers time management from a socio-technical perspective. She considers the underlying assumptions about time, time management, and embedded values, and how they arise from certain aspects of Silicon Valley culture. The author interviewed twenty engineers (tellingly, 18 were male, and all but one were aged 25–40) and noted that the intended users of the calendar app being developed were projections of the developers: ‘knowledge workers who inhabit a work culture in Silicon Valley that is hyper-driven’ (p. 322). The paper highlights embedded values (that time is to be managed, that efficiency and productivity are desired goals, that idleness is undesired). More closely related to our work, Wajcma goes on to briefly consider the vision of a digital personal assistant that can be tasked with managing one’s calendar, and perhaps even with ‘nudging’ the user towards better habits using behavioural science and AI. However, the brief discussion does not consider deployed tools, but rather the views of the developers of the tools, and focuses on the higher-level question of what should the aim of these tools be. Interestingly, DPAs such as Microsoft MyAnalytics could be argued to have somewhat addressed this concern by focusing on empowering the user to reflect and change, in accordance with their own values. However, as we note later in this paper, there is still a concern regarding embedded values that may not align with the user’s values (e.g. meeting time should be reduced).

The reports on the New Future of Work (Teevan et al. 2021, 2022) are a synthesis of research, both from Microsoft and elsewhere, and from a broad range of disciplines, on the impacts of the COVID-19 pandemic, and the associated forced shift to remote work. The 2021 report covers a number of areas including collaboration and meetings, personal productivity and wellbeing, devices and physical ecosystems, and societal implications. Of these, the most relevant is the second: personal productivity and wellbeing. The 2022 report has a different ‘slicing’, focusing on the scale: individual, teams, organisational, and societal.

The personal productivity and wellbeing chapter of the 2021 report highlights that the pandemic and the change to working from home have posed challenges to productivity and wellbeing. The effects have varied depending on a range of factors, such as whether the person had prior experience working remotely, their working from home context (e.g. home office space and equipment, whether other people share the house), and caring responsibilities for others. Broadly speaking, the shift to remote work has, on the one hand, given increased flexibility, which is valued, but on the other hand, blurred the line between work and non-work, making it harder to disconnect from work. This is argued to represent a shift in perspective from 'work-life balance' to 'work-life integration'. Another finding is that the number of hours worked have increased, including in evenings and weekends. Mental and physical health concerns are also highlighted, although some of these relate to the broader implications of the pandemic (e.g. inability to interact socially face-to-face, and the closure of gyms).

Overall, these findings underscore the need for DPAs to help people reflect on their work practices, in order to improve wellbeing, work-life balance (or indeed work-life integration!), and productivity. The report also highlights that there is a strong desire for work to move to a hybrid model, rather than return to being fully in the office or remain fully remote. This means that this need for DPAs to support ongoing reflection and adjustment will remain as the nature of work continues to change. The 2022 report also highlights explicitly that there is a role for technology to play in supporting work-life integration and wellbeing. However, its discussion of the potential of AI is limited to human-AI collaboration, using AI in meetings (to monitor behaviour, and to summarise meetings), and recommendation systems that help foster connections between people, and support knowledge sharing.

The reports find that managers can play a crucial role in helping to reduce the negative consequences of remote work: workers who had more support from their manager in prioritising work had less of an increase in working hours (Section, 2.4.1; Teevan et al. 2021). This particular finding highlights the potential value of the network management tool for managers, in order to ensure that their reports are not neglected. A second finding is that virtual meetings are more fatiguing than face-to-face, which more strongly motivates the need to reduce the number of meetings and to have gaps between meetings. A third is that the 2022 report notes that productivity has a number of dimensions, and that different people interpret it differently; and that wellbeing is also multi-dimensional, and is increasingly important. Both of these findings have implications for how one attempts to measure productivity and wellbeing: the measurement metrics should attempt to take account of these multi-dimensionalities. A fourth is the need to provide support for forming and maintaining social links, especially 'weak ties'.

The emergence of AI in the co-regulation of digital work

An emergent group of information systems combine AI techniques such as machine learning with behavioural analytics to play the role of a coach or co-regulator, supporting users in self-improvement. For example, there are AI-based tools designed to coach people in reaching health-related goals such as weight loss (Stein and Brooks 2017), in games and sports such as cricket (Mandot and Chawla 2013), and in leadership skills (Strong and Terblanche 2020; Terblanche and Cilliers 2020). Other AI-based systems aim to help workers manage workplace productivity challenges that arise from information overload and technostress (Ayyagari et al. 2011; Mazmanian et al. 2013; Tarafdar et al. 2013).

It is in this human-AI collaboration space that AI can play an important and helpful role by supporting human actors to better perform their tasks (Lee 2018). Taking a human-AI collaboration perspective, the class of tools known as Intelligent Assistants (also referred to as AI Assistants, Intelligent Personal Assistants, Intelligent Software Assistants, Intelligent Digital Assistants, or Intelligent Agents) and humans can potentially work together to create a new, higher-level human-machine symbiosis in performing work (Jarrahi 2018). An intelligent assistant (IA) is 'an integrated system of intelligent software agents that help the user with communication, information and time management' (Azvine et al. 2000, p. 215), where they learn from the user as they are performing repetitive tasks, adapting its behaviour to their habits, and improving its performance with minimal intervention (Azvine et al. 2000). Examples include intelligent assistants for organising email (Segal and Kephart 1999); intelligent writing assistants (Oakman 1994); and intelligent assistants for data analysis (Serban et al. 2013).

Microsoft MyAnalytics (MMA)[1] reflects a move from analytics using personal data (Ruckenstein 2014) to using workplace data, i.e. moving from personal analytics to enterprise personal analytics. As discussed later, these tools also leverage research on persuasive information systems: systems that aim to persuade a human to change their behaviour (Oinas-Kukkonen and Harjumaa 2009).

The result is a new class of tools that we term 'Digital Productivity Assistants' (DPAs). These tools use personal workplace data to provide insight and persuasion to help workers improve their productivity and their wellbeing.

In this paper, we focus on the case of MMA which applies machine learning to data created by users' activity in the Office 365 suite to coach users in improving productivity and wellbeing.[2] MMA provides an overview of people's work patterns, such as collaboration behaviour, work hours, and time dedicated to focused work.

MMA also provides actionable advice in the form of suggestions for how individuals can change their behaviour. For example, MMA makes individuals aware of when they spend too much time in meetings or multi-tasking, and suggests that they plan more 'focus time' (time that is free of meetings and other interruptions) in their calendar in advance. MMA analyses a range of information in the Office 365 ecosystem including collaboration (meta) data (e.g. from emails, calendars and Microsoft Teams), employing a range of AI techniques ('AI-powered suggestions', Janardhan 2019). For example, natural language processing is used to analyse email content in order to identify assigned tasks. MMA applies a range of behavioural techniques, such as comparative metrics and evidence-based justifications for particular changes, in order to nudge users towards a desired behaviour. By acting as an analyst and adviser on productivity-related behaviours MMA, and other DPAs, can be seen as emergent collaboration partners for knowledge workers; an application of the emergent phenomenon of machine-human collaboration (Seeber et al. 2018, 2020).

Theoretical lens: co-regulation and technology affordances

Owing to the cognitive and operational capabilities of AI-based platforms (Chiu et al. 2021), intelligent DPAs have the potential to collaborate with individuals in planning, monitoring, and control of thinking, feeling, and actions. AI's automated action supported by natural language processing and machine learning algorithms may, therefore, affect co-regulation dynamics. By analysing individuals' behaviours based on personal and work-related data, AI-based work partners can adapt their intervention strategies depending on an individual's changing context. Nonetheless, it remains unclear how AI performs the role of a co-regulator of work, and how users react to AI when it plays such a role. To understand the relationship between DPAs and human actors, we draw on two theoretical lenses: co-regulation and the theory of technology affordances. We summarise these theories below and explain their relevance to this study.

Co-regulation occurs when an actant (e.g. a teacher, supervisor, peer, or tool) interacts with an individual to support them in the course of that person's self-regulation (Hadwin and Oshige 2011; Allal 2020). Self-regulation is an ongoing process through which people set, attain and maintain goals in the context of self-improvement. This process spans cognitive, metacognitive, motivational, and behavioural dimensions (Allal 2020). Self-regulation is also important in the contemporary workplace where individuals are increasingly expected to self-manage their attention and behaviour amidst competing goals, time constraints, and work climates that emphasize initiative, empowerment and self-management (Lord et al. 2010, p. 562). Self-regulation involves four sub-processes: (1) goal setting, (2) monitoring progress towards the goal, (3) interpretation of feedback derived from monitoring, and (4) adjustment of goal-directed actions and/or of the definition of the goal itself (Allal 2010, p. 349). When deciding whether to commit to a goal, individuals calculate how much effort will be involved in reaching the goals and whether the outcomes will be worth it (Aspinwall and Taylor 1997). Once goals are established, they provide a standard against which performance can be measured through feedback on goal-performance discrepancy (Donovan and Hafsteinsson 2006). Co-regulation may impact any or all of the above four processes, which are cyclical and can occur in any order (Allal 2010). For example, co-regulation may influence goal selection by promoting particular standards (Lord and Brown 2003) and work climates may favour particular goals (Dragoni 2005; Lord et al. 2010). Tools can play a key role in co-regulation. For example, e-coaching systems promote ongoing awareness about a coach's behaviour, thinking, and feelings (e.g. by presenting progress and behaviour) and foster relationships (e.g. personalised messages to motivate the coachee) (Beun et al. 2017).

To understand DPAs' co-regulatory interaction with users we employ the lens of technological affordances. Gibson (1979) introduced the concept of affordances to explain how an environment offers opportunities for action relative to an individual. (For example, an adult-sized seat offers an adult the affordance of sitting). Affordances exist independently of whether they are perceived, and whether affordances are acted on depends on an individual's action capabilities (Gibson 1979). (For example, a baby lacks the action capability to sit on an adult-sized seat). Co-regulation uses co-regulatory affordances to provide individuals with the potential for action and/or constrain their self-regulation (Hadwin et al. 2018). Whether co-regulatory affordances enhance or inhibit self-regulation depends on whether they are perceived and acted on by an individual (Allal 2020).

As we are studying an AI-based co-regulatory system, we draw on the lens of technological affordances, an extension of Gibson's theory (Gaver 1991; Hutchby 2001; Markus and Silver 2008; Leonardi 2011; Majchrzak and Markus 2012; Volkoff and Strong 2013). A technology affordance is a possibility for action that is afforded to actors by a technology (Majchrzak and Markus 2012; Pozzi et al. 2014). It describes what a person with a particular purpose can do with a technology (Majchrzak and Markus 2012), such as sharing information. However, a technological affordance needs to be perceived and actualised by a goal-oriented actor in order to translate into the afforded action. Technological affordances may be perceptible (when perceptible information is available about the action possibilities), hidden (when there is no such information) or false (when perceptual information suggests a non-existent possibility) (Gaver 1991).

Based on the above theories, a DPA can be theorised as providing technological affordances for coregulation, or co-regulatory technological affordances. While a DPA may present functional co-regulatory affordances for improving productivity and wellbeing, these affordances may be perceived by actors as enablers or constraints (or not perceived at all). Further, whether the DPA's affordances actually result in better productivity and wellbeing will depend on the human partner's context, capabilities and goals. AI's automated regulative action may further complicate the co-regulation of productivity and wellbeing. An affordance lens is thus useful to explore the interdependent relation between individuals and the technology in the context of use, including affordances and constraints (Leonardi and Vaast 2017).

Materials and methods

This research uses a unique case study (Yin 2008) within the interpretivist tradition (Walsham 1995). We elected to study the case of MMA as it was a newly deployed system and to our knowledge the only widely-available intelligent DPA that operated in an enterprise-wide setting. Our study is based on two sets of data. The first data set is based on our own use of MMA. It consists of a collection of screenshots and memos representing MMA's full range of functionality and interactions with users. This first data set helped us build an understanding of how this highly novel tool worked and interacted with users. On a weekly basis three researchers involved in this study captured and reviewed the elements the tool used to disseminate insights and suggestions (i.e. a weekly digest, a dashboard, an Outlook add-in, and an inline suggestion add-in). We took screenshots of these and documented suggestions the tool was making to us. This process sensitised us to the study context prior to entering the field and helped us develop an approach to interviewing that covered all aspects of MMA analytics. We complemented this data with secondary data including official documents and online videos provided by the tool's developers.

The second data set comprised in-depth interviews with twenty-eight workers from three organisations (university, IT consulting firm, and technology company) that had implemented MMA.[3] These participants included academics ($n = 12$), academic support personnel ($n = 4$), and IT professionals ($n = 12$) (See Table 1 for details). Their jobs are characterised by high job varieties and high job demands, juggling needs from different stakeholders, evolving requirements, and increased performance expectations. When appraising stressful situations, knowledge workers need to build a reserve of resources to cope with challenges (Lazarus and Folkman 1984; Aspinwall and Taylor 1997; Lin et al. 2015). MMA presents the action potential to achieve their productivity and wellbeing goals. Their view of and interactions with MMA are, therefore, meaningful and informative for our research questions. The interviews were conducted between November 2019 and February 2020.

Table 1. Characteristics of interviewees.

Pseudonym	Gender	Role	Responsibilities	Organisation
Uriel	M	Partner	business development (e.g. networking, strategy & operations) and client deliverables	IT consulting
Brian	M	Systems Manager	management of applications and infrastructure (strategy and operations); management of system specialists (12 team members)	University
William	M	Consultant	Business analysis, project management, enterprise architecture, and consulting.	IT consulting
Bob	M	Technical Problem Manager	Business continuity planning, development of problem-solving processes, problem analysis and solving, team management	IT company
Yusef	M	Dynamics 365 Developer	Requirements elicitation and software development	IT company
Zoe	F	Dynamics 365 Developer	System maintenance, operation, management, and service support (support 32 different systems)	IT company
Alice	M	Consulting Enterprise Architect	Consultancy – IT strategy, IT decision-making, IT implementation and use	IT company
Felicity	F	Research Development Coordinator	Designing and fostering research environments, supporting research activities, and organising research events	University
Xavier	M	IT Services – General Manager	Business development (e.g. networking, strategy & operations) and managing the unit	IT consulting
Jessica	F	Academic	Teaching, research, academic services, admin leadership, external engagement, professional development programme,	University
Tom	M	IT technician	IT services – system administration and IT service support	IT consulting
Victoria	F	consultant	Product and service development, from strategy, planning to development	IT consulting
Liz	F	Academics & leadership role	Teaching, research, academic services, admin leadership	University
Oliver	M	Web and communication advisor	Supporting academics and the faculty with communication activities; analysing and managing social media/web content; responding media inquiries	University
Sarah	F	Academic & leadership role	Teaching, research, academic services, admin leadership, external engagement,	University
Quentin	M	Academic	Teaching, research, and administrative duties	University
Harry	M	Academic	Teaching, research, and academic services	University
Chris	M	Digital Solutions – Associate Director	Management of IT portfolio, programmes, projects, and teams	University
Patrick	M	Academic	Teaching, research, and external development	University
Matthew	M	Academic	Teaching, research, and academic services	University
Isaac	M	Subject librarian	Managing library resources, supporting academics and students to utilise library services and resources	University
Elsa	F	PhD student, research assistant, tutor, and lecturer	Research, teaching, professional services (e.g. editing)	University
Donna	F	Research & Teaching Fellow	Mostly research recently	University
Kathy	F	Academic & leadership role	Teaching, research, academic services, admin leadership, external engagement,	University
Noah	M	Digital solutions – learning technologists	Learning and teaching development and support (focusing on the role of digital tools)	University
Rachel	F	Academic	Research, teaching and administration	University
Ginny	F	Academics & leadership role	Research, teaching and administration	University
Adrian	M	Digital Solutions – Director	IT strategy and operations	University

They were focused on understanding participants' experiences of using MMA and consisted of three parts: (1) exploring participants' general approach to self-regulation of time at work; (2) exploring their understanding of MMA and its value to them and (3) asking them to comment on the most recent report from their MMA dashboard. In combination, these rich datasets helped us understand the co-regulatory affordances of MMA and how workers were reacting to these in practice.

We analysed the collected data using an iterative and interpretive approach (Walsham 2006). First, we coded the screenshots and memos about how MMA presented behavioural analytics and interacted with users. To understand MMA's co-regulatory affordances, we used an inductive process to develop preliminary themes, then returned to the literature and undertook a second round of coding that drew on themes from persuasive design theory. We coded the transcribed interview data using NVivo software to develop a set of themes about users' experiences of MMA. This was a highly iterative process. To enhance reliability and mitigate any bias arising from our personal use of MMA, each interview was independently coded by two researchers. We employed conscious 'bracketing' (Chan et al. 2013) of our own experiences and focused on identifying diverse participant experiences. We interspersed individual coding with meetings to compare and agree on codes and merge them into higher-level themes that represented people's experiences with using MMA. The later stages of this coding process was sensitised by the theoretical concepts of co-regulation and technology affordances and were validated through several iterations until we had reached a point of saturation (no new codes emerged from data analysis) and a consensus was reached.

Results

The first section of the results reports on our analysis of the screenshots and memos capturing MMA's analytics and interaction with users, to identify the co-regulatory affordances that MMA offers users (i.e. the opportunities that it provides for self-regulatory action, and for users to engage with it as a co-regulator of productivity and wellbeing) and how these draw on methods of persuasion. In the second section of the results, we report findings about participants' experiences with MMA and how they responded to its affordances. To place these findings in context we firstly report on the practices that participants used to regulate their work prior to deployment of the DPA. These practices were well-established before MMA was introduced and, therefore, affected their responses to its affordances. Our thematic analysis of participants' experiences then leads us to identify a set of perceived barriers to engagement.

It is notable that most study participants did not act on the DPA's affordances, saw the DPA as presenting constraints, and/or rejected the DPA. Nonetheless a few participants activated the DPA's affordances and reported that working with the DPA helped them transform work practices and achieve positive outcomes relating to their productivity and wellbeing. In our analysis, we, therefore, consider the reasons for these differences between users. We relate our findings to the interdependent sub-processes of co-regulation: goal setting, monitoring of progress towards goals, interpretation of feedback derived from monitoring, and adjustment of (self-regulatory) actions or goals.

Opportunities: co-regulatory affordances of the DPA

We identified four types of technological affordances that the DPA provided for the co-regulation of productivity and wellbeing. These were: (1) Monitoring work patterns and their impact on wellbeing and productivity, (2) identifying and setting goals, (3) automating co-regulation to scaffold habit- and goal-building, and (4) developing contextual awareness of the self and others. These are outlined below.

Monitoring work patterns and their impact on wellbeing and productivity

MMA sent users a weekly email report about their individual work patterns. The report tracked patterns such as the amount of time spent in meetings and reading/writing email, highlighted issues and accomplishments relating to productivity and wellbeing, and suggested foci for attention. (For example, 'Looks like reviewing your after-hours collaboration may be an opportunity because your average is over 4 hours for the past 4 weeks'). The report was linked to a dashboard (which users could also access directly) that provided drill-down analyses of four types of 'work patterns' with accompanying commentary: (1) Focus (time not spent in meeting or email activity as recorded in Outlook), (2) Wellbeing (days protected from after-hours work as recorded in Outlook), (3) Collaboration (time spent in meetings or email activity as recorded by Outlook) and (4) Network (the network of collaborators recorded in Outlook). The report compared individuals' performance in each category to their performance in the previous month and to implicit norms. These affordances can be seen as linked with several sub-processes of the co-regulation cycle: monitoring of progress towards goals, interpreting feedback from monitoring and promoting adjustment of actions or goals. The weekly report can be seen as a scaffolded affordance for individuals to develop a monitoring practice.

Identifying and setting new goals

The DPA also provided affordances for the user to identify and set new goals that related to the four work patterns: focus, wellbeing, network and collaboration. By doing this, and omitting other ways of framing work patterns, it positioned these four categories as those that matter most for managing productivity and wellbeing. This can be seen as drawing on the principle of reduction from persuasive information systems design (Fogg 2002; Oinas-Kukkonen and Harjumaa 2009), i.e. reducing complex behaviour into simpler tasks, which can increase the benefit/cost ratio of a behaviour. Each work category was linked with a rhetorical question invoking the user to review the DPA's analytics and suggesting candidate goals; e.g. 'Do you have enough uninterrupted time to get your work done?', 'Could your time working with others be more productive?' These rhetorical questions implied that new goals were needed and employed gain framing (outlining the gains that would result) to make these goals seem desirable.

When users drilled down to see more detailed analytics, the DPA presented a series of normative suggestions relating to implicit goals. For example, in a breakdown of meeting-related behaviours, it analysed performance against '[Meeting] Invitations sent with a day's notice' and '[Meeting invitations] sent with an agenda'. The tool's 'suggestions' combined normative framing with imperatives, such as 'Respond to meetings on time'. The associated dialogue elicited goal-setting. For example, the statement, 'Looks like you worked in your quiet hours for more than 7 hours per week over the past month' implicitly suggested that users should aim to reduce time spent in after-hours meetings. The Wellbeing section of the dashboard asked, 'Are you able to disconnect and recharge?' and showed the number of 'quiet days' – days that were 'protected' from after-hours meetings or email handling. When users clicked the question-mark icon beside each monitoring category they were given short explanations of 'How it works' (i.e. where the monitored data came from) and 'Why it matters' (the rationale for this aspect of self-regulation). For example, the Wellbeing section stated, 'People who disconnect daily from work report lower levels of stress and anxiety', the Focus section noted, 'It can take up to 23 minutes to focus after checking just one email or chat' and the rhetorical question, 'Do you have enough time to get your work done?' The combination of these features created goal setting affordances.

Automating co-regulation to scaffold habit- and goal-building

Another affordance of the DPA was automating the co-regulation of work. Through automated actions, this affordance reduces the user's cognitive efforts and supports a shift in productivity/wellbeing with little behavioural change. For example, users were offered a tool to automate the booking of two-hour blocks of daily focus time optimised around existing commitments. If users deployed this tool (via a single click) a weekly cycle of self-monitoring of focus time was triggered, with the tool reporting it in its weekly digest, 'here's how you're doing on your plan to get daily focus time'. In other words, an explicit goal (having a 'plan' for focus time) was triggered by the deployment of the tool. This can be seen as using the persuasive design principle of tunnelling (guiding users by providing a means for action that brings users closer to the target behaviour) (Fogg 2002; Oinas-Kukkonen and Harjumaa 2009). Similarly, a 'shorten meeting' button encouraged users to shorten one-hour meetings to 45 minutes in a single click. These examples show the use of nudging and choice architecture (Thaler and Sunstein 2008). The DPA limited users' available choices while making readily available more 'desirable' choices (i.e. having shorter meetings, and automating the booking of focus time).

When activated, the automated co-regulation tools triggered monitoring by MMA, which can be seen as affordances to foster habit- and goal-building. For example, once the focus time booking tool was enabled, the DPA's weekly email started to report on the user's 'focus plan'. This is an act of reframing in which the reactive deployment of automation is recast as part of a deliberate strategy; in this case, to have, and monitor, a weekly 'focus plan'. Selecting the automation tools can also be seen as activating the peripheral route of attitudinal and behavioural change (Petty and Cacioppo 1986) – in which the user responds to a positive cue without engaging with the underlying logic – in pursuit of a higher-level change goal (making the monitoring of focus time a new goal or 'plan'). The reframing (i.e. the DPA's report on 'your focus plan') implies an elevated level of agency on the user's part and can be seen as designed to appeal to the central, goal-directed system of change (Petty and Cacioppo 1986).

Developing contextual awareness of the self and others

The DPA had several affordances for building contextual awareness of self and others. These were geared toward generating new perspectives that would foster new behaviours and norms to facilitate the wellbeing of self and colleagues. The DPA's analyses of time use can be seen as designed to draw users' awareness to their attentional focus – both in terms of how they spent time and who they spent it with. The DPA's reports paid particular attention to the times spent in meetings – including how many people were in the meeting and whether multi-tasking was occurring during the meeting. The network analysis reported on the amount of time that individuals spent communicating and meeting with specific key people (i.e. those who regularly emailed or met with them). This allowed ready identification of people who made excessive time demands and drew attention to the equity of distribution of time to those deemed as being 'important'. (This was inferred by the tool but users could assign or unassign colleagues as being 'important'). Another metric reported on 'top after-hours collaborators'. This highlighted those whose personal lives might be interrupted by interactions, or who were causing such interruptions. The DPA's tools for automating the booking of focus time and the delayed delivery of emails that were sent after-hours were affordances for fostering improved awareness of wellbeing at a team level. For example, if an email was composed after-hours, the DPA prompted the user to enable a feature to delay the email delivery until the recipient's working hours.

These affordances can be seen as calling on the principle of reciprocity – i.e. if workers look out for their colleagues they are more likely to look out for you. In this way, the DPA had affordances for the normalisation of collegial concern and individual contributions towards the management of collective wellbeing.

Self-regulation of work prior to the DPA's deployment

Before reporting our findings on the study participants' responses to the DPA, we outline the practices that they used to manage productivity and wellbeing prior to MMA's deployment. This is important to help understand their experiences of the DPA, which offered affordances for doing things they were used to doing on their own.

Participants reported having a range of well-established practices for managing their productivity and wellbeing prior to engagement with MMA. Common practices included reserving time for priority work, shifting meetings to make gaps for key tasks, booking time for exercise, assigning restricted times for checking email, and planning to work from home on certain days to minimise disruption. Participants spoke of managing their time in relation to categories of work that were meaningful to their role; for example, service-line managers spoke of allocating time to clients and their direct reports, while university academics placed a strong emphasis on making time to do research, something they found challenging due to the competing pressures of teaching and administrative work that often presented more urgency. The goals guiding these practices were implicit but related to using time effectively, getting priority work done, and improving work-life balance. Participants did not monitor their progress against these implicit goals and had no ready means for doing so. Nonetheless, they had a sense of how they were tracking against their goals.

It was notable that some participants felt that they had little control over their use of time. Those who held dual roles as academics and senior administrators expressed particular difficulty in regulating their work. They explained that they needed to work around other peoples' availability and/or they found themselves overriding the time planned for doing important work with more reactive, urgent tasks. They were aware of goal-performance discrepancy, but felt that they had little ability to address this, and normalised a long working week. For example, Liz,[4] an academic who holds a senior leadership role, said that her 70-hour weekly average was inevitable due to the deadline-driven nature of the role, her organisation's processes, and the high level of detail in her administrative work. Kathy, an academic who holds a senior leadership role, reported that she had 'failed miserably' to find time for research despite engaging a mentor and trialling different time-management strategies. She periodically reviewed weekly calendars that she had printed out, to get 'a gut feel' for the negative impacts of the administrative part of her role, but said that doing this did not inform her planning. Such individuals might be expected to gain benefit from a DPA. However, as we report below, they were unable and/or unwilling to take advantage of the DPA's co-regulatory affordances.

Barriers: responses to the DPA's co-regulatory affordances

When MMA was deployed within Office 365, a new AI-based actant unexpectedly entered the private contexts in which participants self-regulated their productivity and wellbeing. It presented them with unfamiliar analyses of their work habits, and unsolicited affordances and suggestions for change. This was not well received by many participants who expressed concern about the lack of warning, low accuracy, limited relevance of the data presented by MMA, and unease about being monitored. Although the DPA offered new means of managing productivity and wellbeing, most participants did not act on the DPA's affordances, saw the DPA as presenting constraints, and/or rejected the DPA. Nonetheless, a few participants activated the DPA's affordances and reported that working with the DPA had helped them transform work practices and achieve positive outcomes relating to their productivity and wellbeing. In our analysis, we outline the key perceived barriers to engagement with the DPA that emerged from our thematic analysis of participants' experiences, and consider the reasons for differences between users. We relate our findings to the interdependent sub-processes of co-regulation: goal setting, monitoring of progress towards goals, interpretation of feedback derived from monitoring, and adjustment of (self-regulatory) actions or goals.

Our analysis of the interview data identified three high-level barriers experienced by participants in relation to working with the DPA: These were: (1) a mismatch between the experienced reality of work and the data and analyses presented by the DPA, which excluded interactions that occurred outside of Office 365, (2) terminological and conceptual differences between users' perspectives and those presented by the DPA, including the way in which the DPA assigned reductive categories for the use of time (focus time vs. collaboration time), which lacked relevance to role-specific activities, and (3) the amount of time and effort involved for participants to interpret the DPA's feedback and monitoring, which created a new role demand.

Barrier 1: mismatch between experienced reality of work and view presented by DPA

Many participants reported that the view of their work habits presented by MMA did not match their experienced reality. They recognised that the DPA had no visibility to work activity that was not recorded in Office 365, such as impromptu in-person (or zoom) meetings and calls. For example, Tom, IT technician, indicated the biggest shortfall of MMA is its inability to capture real office interaction.

> One thing that a tool like this will never indicate is real office interaction where you, somebody stands up, walks to a whiteboard and say let's discuss this because it's not a scheduled meeting, so there's no electronic record of it. So where it says I'm available to focus, I might have been sitting here for an hour as you have a conversation on a physical whiteboard. So there's no way to measure it unless you actually physically put it into a tool.

Kathy also stated: 'It's giving me a reflection of my Outlook calendar, which is not a reflection of my work life'. Many of her meetings were not recorded or not counted by the DPA, with the result that the DPA showed Kathy that she had 68% of her time available for 'focus time' yet she felt that she had significantly less time than this available to focus on key tasks. The strong cognitive dissonance between Kathy's lived-in reality and the situation shown by the DPA can be seen as creating a major disincentive to working with the DPA. Making sense out of the DPAs analytics in such situations required significant time and cognitive load, and may not be possible without the user having a mental model of how the DPA's data is collected and categorised, and how its insights are calculated. As the DPA could not adjust to Kathy's work practices, MMA's data and analytics could only be improved if she changed her diary-management practices in Outlook. Most participants reported similar concerns.

Barrier 2: mismatch between the DPA's reductive categories and those used by workers

The DPA introduced new terminology and reductive categories for the use of the time that did not map onto the established role-related categories and concepts that participants used to think about their use of work time. For example, academics reported assigning their time to three categories – teaching, research and administration. However, the DPA assigned all time to either 'focus' or 'collaboration', and did not support user assignment of time to personally-meaningful categories. Many participants reported being confused by the fact that MMA assigned their work time to two mutually exclusive categories ('collaboration' and 'focus time'). This was especially problematic for those who saw collaboration as part of their focused work, such as collaborating on projects. Felicity, a research development coordinator, noted,

> I guess anything like that is going to be very blunt and it's going to make assumptions about what you're doing … It assumes that meetings are collaborative. It assumes that time outside of meetings is focused time, it makes all sorts of assumptions … [and] given the bluntness of the instrument … I'm less inclined to take it seriously.

Uriel, a partner of an IT consulting firm, further questioned the arbitrary compartmentation between 'focus' and 'collaboration'.

> For any meeting you turn up to, like if you're a, meetings orientated person … a productive meeting normally you put an hour before and an hour after, as a general rule of thumb. Otherwise why are you there? So to me in my sort of role it [MMA's presentation] is slightly skewed, it [any meeting] should be more 33% collaboration time and 66% focus time.

This situation was compounded when MMA suggested the goal of protecting more time for focused work by reducing the time spent on collaboration. Further, the terminology used by the DPA for categorising time was often not well understood. In some cases, interviewees understood the DPA's concepts, such as 'focus time'. However, in other cases, people consistently misinterpreted a concept. For instance, 'quiet time' was often interpreted as 'a day that was not too busy', whereas the DPA used it to mean 'a day where work was only done during the defined working hours'. In such situations, the DPA's intended affordances (such as automating the booking of 'focus time') and use of reduction (assigning all time to two categories) (Oinas-Kukkonen and Harjumaa 2009) acted as constraints, and/or the affordances were perceived as false affordances (Gaver 1991).

Barrier 3: time-consuming new role demand: interacting with AI

Many participants reported that the effort required to understand the DPA's analytics and/or improve the accuracy of data it drew on was onerous and stressful. This work can be seen as creating a new role demand: workers now needed to interact with an AI-based work partner, the DPA, which lacked insight into their work and depended on them for quality data inputs. For example, a few participants took on this role and started using the Outlook calendar more intensively and in ways that the DPA would 'understand'. This extra work, and the role of partnering with the DPA were rejected by those unwilling to take on the extra cognitive effort. Ginny, an academic programme director, stated: 'I don't think I'm going to go into the dashboard and have a look at it because it doesn't actually tell me what I can do'. In such cases, the DPA's affordances can be seen as effectively remaining hidden (Gaver 1991) to those who were unwilling to contribute interpretive efforts.

We now turn to cases where participants triggered the affordances, finding them useful.

Affordances as opportunities

Despite the above issues, a few study participants engaged strongly with the DPA's co-regulatory affordances, and actively used (activated) these to change their work patterns and gain benefits in their productivity and wellbeing. Table 2 summarises how individuals activated each of the affordances to make changes to their work practices and thereby increase the frequency and/or scope of their self-regulation of work (productivity and wellbeing).

Notable among these was Brian who worked in an IT management role and had a good understanding of how the DPA worked. Brian emphasised that while he saw it as a 'dumb tool' he could get value from the DPA by putting effort into working with it – this involved him making efforts to interpret the way in which the DPA reported his time use, and to ensure that meetings were recorded in his diary. Brian also booked focus time in his diary, making this visible to the rest of his team, and cultivating a group norm that these blocks of time could be interrupted only if absolutely needed:

> Although it's focus time and it's available to me to be able to focus, I've left it there and I don't call it anything else. I don't, I block it out. People quite often impinge on that focus time, […] I've told them that's okay as long as they're not doing it to any great degree because I am trying to get things done.

Similarly, Uriel, who worked in a business development role, reported having to work to gain value from the analytics that the DPA showed him: 'You've sort of got to dig into

Table 2. Activation of the affordances in new work practices – examples.

Affordance	New practice arising from activation of the affordance
Monitoring progress	Reading weekly reports reviewing the DPA dashboard; Taking time to interpret and make sense out of the DPA's report and evaluate the implications
Identifying and setting goals	Working to plan weekly focus time; Identifying goals (e.g. increase focus time, reduce out-of-hours work, shorter meetings, improved meeting practices such as sending meeting agenda in advance)
Automating co-regulation to scaffold habit- and goal-building	Automating booking of 'focus time'
Developing contextual awareness of self and others	Reducing the frequency and duration of meetings with people who were perceived to be using too much time; normalising the protecting of focus time at team level (making it inappropriate to book meetings across designated focus time); asking the CIO to delay sending urgent midnight emails to system administrator

that information and … you've got to know what questions you're going to ask before you can use it usefully'.

Another participant retrospectively added meetings and changed their duration in Outlook to reflect what had actually happened. These were new co-regulatory practices performed by humans for the DPA. In other words, humans were doing a new type of work for the AI so that the AI would have better data and perform better for them. Those who did this work had a sense of the reciprocity involved. They recognised that these efforts were required to successfully activate the DPA's affordances and optimise their value.

A few participants used the MMA Networking feature to actively review how much they interacted with key people. Comparing how much time they spent interacting with different people allowed participants to identify those who were consuming an unusually high amount of their time, or who were not receiving the attention that was needed.

> It [the MMA Networking feature] could highlight to me if I'm spending time with people I shouldn't or don't need to or too much, you know, someone's here when they should be back here … Why am I spending so much time with Susan? You know, she's a STM that works way down in the bowels of our business. It'll get me questioning why. (Xavier, IT Services General Manager)

We also found a larger number of participants who, despite not being engaged strongly with the DPA, found aspects of the DPA useful. These aspects include the tool's broad goals relating to wellbeing, and responding to specific suggestions, such as planning shorter meetings.

Discussion

We now generalise our findings by considering how they apply more broadly to other settings. We frame our discussion under three main areas: (perceived) accuracy, transparency, and feedback (including configurability).

Perceived accuracy

The perceived accuracy of information is the extent to which the DPA is seen as providing an accurate representation of the participant's (relevant) work activities.

For example, when a busy academic or professional is told by the DPAs that they have 80% of their time available as 'focus time' this immediately creates a negative first impression. If a tool's information is not seen as accurate, then the tool will not be trusted.

The DPAs' perceived accuracy is influenced by the coded-in 'assumptions' of the DPA. For example, a calendar appointment with no other people listed is not deemed to be a meeting (this was often incorrect in reality). Conversely, Jessica, an academic, had a 'meeting' that was actually a silent writing group (i.e. focus time). Additionally, the DPA's assumptions that 'collaboration = meetings' and that 'time = collaboration + focus' are questionable. The former is arguably old-fashioned, and at odds with newer ways of working (such as encouraged by MS-Teams). The latter ignores the possibility of other valid uses of time at work. For instance, giving a lecture is neither collaboration nor focus.

Interestingly, when the participants' experience of focus time diverged from that shown by the tool, they expressed dissatisfaction with the tool's accuracy (rather than seeing this as an insight into their own time management). However, participants reacted very differently when the tool accurately revealed the amount of time they had spent on using email (this was reported in the 'wellbeing' category). The fact that the problem was visualised/externalised and quite accurately quantified appears to make it easy to internalise as a self-regulation issue, whereas in the case of focus time, the 'problem' was cast as being the tool's accuracy.

The perceived accuracy of information was related to certain workplace practices. On the one hand, the work done outside the Office 365 ecosystem is invisible for the tool (e.g. using a different calendar, or chat messenger instead of Outlook) and will decrease the tool's accuracy.

On the other hand, when people used the Outlook calendar and Outlook email exclusively (for work), and understood the concepts, they generally accepted the tool's view as correct (in some cases except for ad hoc meetings).

More broadly, the lesson here is that any AI tool development and deployment needs to consider not just the accuracy of the data, and of the tool's recommendation or behaviour, but also to what extent the data and the tool are perceived as being accurate. A perception of inaccuracy can occur even if the tool is accurate but there is a difference in conceptual understanding. Perceived accuracy can be aided by transparency, which we turn to next.

Transparency

Transparency can be defined as 'being able to understand the ways systems make decisions and the data being used' (Dignum 2019, p. 51). In order to trust a system, it is important to understand to some extent how it reaches conclusions, what information it uses, and even what concepts, terms, and assumptions are being used. Transparency is important because even if the information is seen as being accurate, a lack of transparency can undermine credibility (Lewis et al. 2018, p. 140).

The DPA does not provide a way for a user to interact with it in order to understand why it is making a specific recommendation, or how a certain displayed observation has been derived. When the tool estimates the time available to focus, the user cannot easily find out the basis for that estimate in terms of definitions, concepts, assumptions, and data used. One participant, who worked in consulting, noted,

> Yeah so the focus, 60% available to focus. Yeah, that's an interesting one because I think once again, when I look at these sorts of things, I go, well, how does it actually figure out what focus time is or what's not focus time? […] how does it calculate that? How's it going? Otherwise it kind of doesn't sound right, and within what hours? (Uriel, Partner – IT consulting firm)

Transparency applies to a range of aspects of the DPA's co-regulation including:

- Concepts: what does the DPA mean by various terms (such as 'focus time', or 'quiet days')?
- Processing: how does the DPA interpret what it sees? How is particular output derived by the DPA, and how should the user interpret it?
- What assumptions is the DPA making (e.g. that appointments with no other invited participants are 'focus time')?

Transparency also applies to norms and values. The DPA has embedded (and implicit!) norms and values (e.g. meetings should be reduced; more focus time is good). These values are not necessarily wrong, but they may apply differently to different contexts. They may be appropriate for a knowledge worker, who is primarily working alone, but less so for an HR manager whose job requires frequent meetings with other people. In addition to conflicts between the embedded norms of the tool and the user's norms, there can also be inconsistencies amongst the tool's norms. For example, the DPA's metrics and messages encourage the user to reduce time spent in meetings, but also to reduce the number of emails, which together imply limited opportunities for collaboration.

It is worth noting that these findings apply not just to the specific context that we investigated (MMA), but also more broadly to a range of other intelligent systems. Indeed, transparency is also discussed in the broader AI literature on accountability (e.g. Dignum 2019), and there is a sub-field dedicated to explainable artificial intelligence. One important finding of our study that applies more broadly is that transparency needs to be interpreted quite broadly: it's not just about explaining recommendations or behaviour, but can also be about explaining concepts, assumptions, norms and values that are embedded (implicitly) in the tool.

Feedback & configurability

Finally, our analysis, through the lens of co-regulation, highlighted a few key points relating to the use of these systems. Viewing systems such as MMA as co-regulatory partners highlights that there is a key feedback loop missing: there is no way for the worker to provide feedback to the tool about the interaction, or about the user's concepts. Effective co-regulation is hindered by this lack of communication from the human to the system. The system can only observe human behaviour, which gives an indirect and limited view. The co-regulation is also hindered by limited communication from the tool to the user. The tool provides a range of messages, but these are unidirectional, and do not permit a dialogue. This need for richer bidirectional communication is a key finding.

One particular form of feedback needed is the ability to configure the system. For example, rather than have DPA assume that a meeting with no participants is focus time, the user could override this, specifying that a certain meeting is actually collaborative, even though other participants are not recorded in the calendar. Similarly, rather than assume that there are only two categories of meeting (focus and collaboration), it would be useful to define role-specific categories (e.g. teaching, research, service for an academic).

More broadly, providing the user with the ability to provide feedback, and to configure aspects of the tool, can reduce the mismatch between the tool (including its assumptions and concepts), and the user's view of the world. It can also give people using the tool more of a feeling of having control.

Privacy

The reader might be surprised to find privacy last, and not featuring prominently. The reason is simple: privacy (and more broadly ethics) was not seen as an issue by most participants. This can be explained by the fact that in the design of the MMA, there was enough attention given to privacy, including being very clear that insights were only available to the person on whose data they were based on. This meant that the possible concern about one's line manager having access to detailed monitoring of their reports was not actually seen as an issue for the MMA.

Synthesis

Summarising the discussion above, those who perceived the co-regulatory affordances were those who put more effort into working with the DPA, and saw it as useful. On the other hand, if users were cognitively entrenched (Dane 2010) and held negative emotions toward AI (Zhu et al. 2021), then the DPA's weaknesses in accuracy, transparency, and configurability were perceived as constraints. This confirms that collaboration with AI needs to be two-way and that humans need to be aware of the needs and limitations of emerging AI-based systems and willing to adapt to the new type of collaboration (Zhang et al. 2021).

Developers need to consider the implications of 'framing' that is built into an AI-based system. In this study, the goal categories that were monitored were highly abstract and rigid (i.e. focus, collaboration, wellbeing, and networking), and did not map readily onto the way in which people framed their own use of time. A lack of compatibility between technology and users hinders acceptance and adoption (Karahanna et al. 2006). We suggest that the design of the DPA be accommodating and adaptive. Previous research on expectation adjustment techniques, such as giving the user control over the amount of control AI should have (Kocielnik et al. 2019), could help guide the design of future DPAs.

Conclusion and outlook

Drawing on the lens of co-regulation and technology affordances, this study has analysed the emergence of human-AI collaboration in the context of co-regulation. We reveal opportunities and perceived barriers involved in AI acting as a co-regulator. Analysis of the data from twenty-eight interviews and the IT artefact (MMA) identified four types of affordances: (1) monitoring work patterns and their impact on wellbeing and productivity, (2) identifying and setting new goals, (3) automating co-regulation to scaffold habit- and goal-building, and (4) building contextual awareness of the self and others.

Besides the design of the DPA, it is important to consider dynamic co-regulation processes involving individuals and other factors (e.g. organisational contexts and cultural influences) (Hadwin et al. 2018). Individual differences such as motivation, abilities, and adaptation styles affect engagement in co-regulation (McCaslin and Burross 2011). Self-regulation skills, such as goal-setting (goal clarity, goal acceptance, and goal commitment), deserve further attention. Previous research showed that learners with excellent self-regulation skills rely less on co-regulation (Räisänen et al. 2016). In this study, we did not assess self-regulation skill level but observed that many participants did not have clear productivity and wellbeing goals. Future research can examine the role of self-regulation skills in the co-regulation processes to understand if self-regulation still exerts similar effects when an actant is a tool instead of a human. Organisational contexts (e.g. structure and work design) can also be considered to unravel complex processes of co-regulation. A social view of co-regulation maintains that co-regulation is affected by the social expectations, processes and structures where self-regulation and co-regulation activities occur (e.g. Volet et al. 2009). Researchers can investigate whether setting up a clear role description and expectation for the DPA can build swift trust between humans and AI (Meyerson et al. 1996). Additionally, since it takes time to engage with DPAs, learn how to use them, and to adapt practices, encouragement, support, and institutionalised incentives are important (for example, training, paid time, and rewards or other recognition). Furthermore, similarly to human-human collaboration, an accurate understanding of each other (Huber and Lewis 2010) is a key to enhancing collaboration effectiveness. On the one hand, the AI system needs to be trained with appropriate data sets to increase accuracy. On the other hand, humans need to learn to understand the DPA's co-regulation terminologies, concepts, and processes (Ezer et al. 2019), which emphasises the role of explanation in a broad sense.

Our findings based on analysing and theorising empirical materials can be generalised to organisations who intend to introduce MMA to enhance the productivity and wellbeing of workers whose job demands and job variety are high. Moreover, our research demonstrates naturalistic generalisability and transferability (Smith 2018) by offering rich discussions around the IT artefact and individual experiences. This allows the reader to reflect on their experience and assess if the research results can be transferred to their context. However, it should be noted that many participants in our study had neutral or negative attitudes toward MMAs, which is common in adopting disruptive technologies at the early stage (Zhu et al. 2021). Future research can explore DPA's co-regulatory affordances and investigate how affordances are actualised by involving users who perceive DPA's affordances as opportunities instead of constraints.

Our study has presented a case of 'AI in action' – an AI-based tool that is emerging as a co-regulatory change agent in the workplace. In this sense, it can be seen as presenting an early view of 'lived in AI'- AI, as experienced by the workers, positioned to assist in managing issues of personal productivity and wellbeing. Importantly, our study has explored the emergent partnering of AI and human workers and identified perceived barriers to this. As the ongoing sensemaking of AI continues, we call for more research to enhance human-AI collaboration for the regulation of productivity and wellbeing at work.

Notes

1. MMA was further developed and merged into the product Viva Insights as we completed data gathering.
2. Illustrative examples can be found at https://docs.microsoft.com/en-us/viva/insights/personal/use/dashboard-2.
3. The research received all necessary ethics approvals.
4. Hereinafter pseudonyms.

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