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ABSTRACT[1]

There is an emerging shift in HCI research from things to events and toward time and temporality as a design material, which is made even more urgent by the unique time of the Covid-19 period. This paper pushes this shift forwards by investigating factors and the way that these shape online media multitasking behaviour over time during Covid-19. We model the factors along the WHAT and HOW dimensions of the HCI-over-Time model (HCIoT) with self-report data from 117 university students and objective behavioural data from 40 university students, who participated in an online course over two weeks during Covid-19. The results indicated a pervasiveness of media multitasking behaviour over time in an online course, driven by individual factors and enhanced by their mutual fit. Based on interpretation of our data, we suggest conceptualising the Covid-19 period as the larger temporal environment in the HCIoT model. The discussion further explains how the broader idea of human-computer-environment fit is significant to understand HCIoT through an interaction lens. We discuss methodological issues related to differentiating between self-report and behavioural measures when applying the HCIoT model. The conclusion supports the feasibility and significance of conceptualizing media multitasking during Covid-19 as temporal HCI, and of further developing and operationalising the HCIoT model by using both behavioural and self-report measures.

Keywords

Media multitasking behaviour; temporality; Human-Computer Interaction over time; HCIoT model; motives for media multitasking; nomophobia; environmental demands; human-computer-environment fit.

[1]Abbreviations: HCI-over-Time (HCIoT); Uses and gratifications theory (UGT); motive for media multitasking (MMM); 'nomophobic design'/nomophobia (NP); environmental demands on media multitasking (ED); media multitasking index (MMI); media multitasking percent (MMP); fit index (FI); coronavirus disease of 2019 (COVID-19); forms of media (FOM); time spent on media multitasking (TMM).

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1. Introduction

During the Covid-19 period's new remote work paradigm, media multitasking became a common phenomenon (Lee, Park, Lee, & Lee, 2022; N. Matthews, Mattingley, & Dux, 2022). In general, multitasking is an important human-computer interaction (HCI) topic. It is defined as when a person performs more than one unrelated computer-based task concurrently, that is, computer based multitasking is a function of time allocation decisions (Benbunan-Fich, Adler, & Mavlanova, 2011). Multitasking in HCI includes literature on multitasking and interruptions during work (Mark, 2015), multitasking during leisure watching TV and movies (Brumby, Du Toit, Griffin, Tajadura-Jiménez, & Cox, 2014; De Feijter, Khan, & van Gisbergen, 2016; Maruyama, Robertson, Douglas, Raine, & Semaan, 2017; Rigby, Brumby, Gould, & Cox, 2017b, 2017a; Shokrpour & Darnell, 2017; Wei Liang Kenny, Rigby, Brumby, & Vinayagamoorthy, 2017), also called 'second screening' (Kusumoto, Kinnunen, Kätsyri, Lindroos, & Oittinen, 2014; Lohmüller, Eiermann, Zeitlhöfler, & Wolff, 2019; Lohmüller & Wolff, 2019), multitasking during chatting (Suh, Bentley, & Lottridge, 2018), multitasking and distraction and recovery (Hossain, Wadley, Berthouze, & Cox, 2022; Lyngs et al., 2020) and with a clear focus on Covid-19 (Lee et al., 2022), multitasking and life experience (Rapp, 2022; Santarius & Bergener, 2020), and media multitasking and academic student activities (Leysens, le Roux, & Parry, 2016; Lottridge et al., 2015; Park & Liu, 2012; Whittaker, Kalnikaite, Hollis, & Guydish, 2016). The topic of our paper falls into the latter category, as it is about media multitasking in an online university course during the Covid-19 period in China.

HCI research on time use on media multitasking among students in higher learning institutions indicate that the phenomenon is widespread and problematic. To establish the use of time in media multitasking, recent HCI studies (Lottridge et al., 2015; Lyngs et al., 2020; Whittaker et al., 2016) refer to a Computers in Human Behaviour-study by Rosen et al. (2013) that says that university students on average tend to switch tasks every 6 minutes and that university students were on-task 70-72% of the total time, that is, doing other activities 28-30% of the time. Hence, media multitasking is an important phenomenon for HCI time and temporality studies (Wiberg & Stolterman, 2021). In comparison to the scheduled activities, the modern daily life has more spontaneous and opportunistic ones with demands for 'plastic' technologies that have been integrated into the heterogeneous rhythms of daily life and support multitasking (Rattenbury, Nafus, & Anderson, 2008). Previous studies have shown that engaging in multiple media simultaneously or sequentially is prevalent among young university students due to the ubiquity of media technologies (Parry & le Roux, 2019; Rosen, Carrier, & Cheever, 2013). This phenomenon, coined 'media multitasking,' describes the behaviour of engaging in two or more media (e.g., text messaging, social media, music, games) simultaneously or sequentially during a given period of time (Circella, Mokhtarian, & Poff, 2012; Karpinski, Kirschner, Ozer, Mellott, & Ochwo, 2013; Kirchberg, Roe, & Van Eerde, 2015; Salvucci, Taatgen, & Borst, 2009). Furthermore, in the case of online learning, media multitasking can be defined as the phenomenon of simultaneously or sequentially engaging in multiple activities related or unrelated to an online course during said course. A recent study showed that self-reported multitasking was significantly greater in online than face-to-face courses (Lepp, Barkley, Karpinski, & Singh, 2019). Despite the pervasiveness of media multitasking behaviours thanks to the emergence of technologies (e.g., plastic technology, multi-screen, multi-device,) in supporting media multitasking, media multitasking during academic activities has been found to be associated with lower academic performance and test scores (Rosen et al., 2013; Wood et al., 2012; for a review see Van Der Schuur et al., 2015). A meta-analysis of the relationship between smartphone use and learning showed that multitasking in class was associated with a significant deleterious effect that is significantly different from excessive texting and excessive phone use (Sunday, Adesope, & Maarhuis, 2021).

The Covid-19 situation offered unique motivation and opportunities to study empirically media multitasking over time in online environments. It is particularly important to understand and explore in a situation in which students were isolated and participating in online learning how they were multitasking during online teaching. In the spring of 2020, universities worldwide were required to suspend face-to-face courses as one of the necessary measures to contain the spread of the coronavirus disease of 2019 (Covid-19). To help maintain continuity of educational activities that were suspended due to the outbreak of Covid-19, many off-line classroom courses were moved online owing to sustainable networks with Internet access and emerging cutting-edge technologies (e.g., cloud computing, Internet of Things). For instance, 24,000 online university courses were provided on 22 platforms in early 2020 in light of the nationwide pandemic in China (Sun, Tang, & Zuo, 2020). The students studying in places with outbreak of Covid-19 and its' variants took online courses in the spring of 2021 again and spring of 2022. This long Covid-19 period with forced online learning activities offered a window to investigate the effect of the pandemic on students' behaviours, specifically media multitasking behaviours, and values in relation to online learning technologies through a temporality lens. Covid-19 induced students to do most of their tasks online, computing devices rapidly offered more functionality and helped ordering the new way of online life, and so the human-computer interactions that took place during the Covid-19 period were clearly more online than what the world has seen before. We took the opportunity provided by the Covid-19-period to study students' media multitasking in online courses.

At the same time, theoretical development in HCI over time research made students' media multitasking over time in online course during the Covid-19 period a timely and important phenomenon to study. By developing a Human-Computer-Interaction-over-Time (HCIoT) model, Wiberg & Stolterman (2021) managed to synthesize an overview of findings from the HCI literature on the time and temporality aspects of HCI in a 4 × 4 matrix. The four columns represented subcategories of a WHAT dimension of HCI time and temporality: the Human (collective and individual dispositions for rhythms, sequences, etc.), Computer (fundamental temporalities of digital life), Interaction (pace of human-computer synchronization) and over Time (larger temporal environment of HCI such periods, phases, waves of HCI). The four rows in the HCIoT model represented the Empirical (e.g., multitasking behaviour), Methodological, Theoretical (e.g., time sharing designs), and Design subcategories of a HOW to study dimension. Thus, Wiberg and Stolterman with the HCIoT model analysed HCI time and temporality at the intersections WHAT to study and HOW to study. We found that this offered a pragmatic, design-oriented, and holistic approach to capture the essence of the phenomena of media multitasking during Covid-19. Covid-19 obviously was (still is at the time of writing this paper) a special period that has motivated and enabled media multitasking on a new level never seen before. Furthermore, the strands of research on multitasking are characterized by a focus on time optimization. Finally, it was from early on one of the focuses of time and temporality studies in HCI (Wiberg & Stolterman, 2021), so we help fill an identified gap in the literature. In addition, since our study was done in China, we also contribute to meet the call to "expand to an Asian context to further develop an international network of researchers and practitioners investigating topics of time, temporality, and slowness" (Odom et al., 2018).

In this paper, we contribute to the first wave of time and temporality studies in HCI by examining whether the four subcategories of the WHAT dimension in HCIoT model may help explain the media multitasking behaviour during an online course amid Covid-19. Besides, the second wave of time and temporality studies in HCI denotes a new direction for the development of methodologies for data collection and analysis with a temporality lens (Wiberg & Stolterman, 2021). We contribute to the second wave by showing HOW a combination of both self-report and objective behaviour of media multitasking can provide different and holistic understandings of the temporal aspects of HCI. Together, this helps to explore media multitasking in the Covid-19 period as a HCI phenomenon.

2. Literature Review

Surprisingly little HCI research on time use on media multitasking among students in higher learning institutions exists. Recent HCI studies (Lottridge et al., 2015; Lyngs et al., 2020; Whittaker et al., 2016) refer to a Computers in Human Behaviour-study by Rosen et al. (2013) that says that university students on average tended to switch tasks every 6 minutes and that university students were on-task (reading book, reading appropriate website, writing on paper and writing on computer) 70-72% of the total time, that is, doing other activities 28-30% of the time (off task was: Facebook, IM, texting, television, music, eating and walking/stretching). When evaluating their novel design, a multitasking awareness tool, Whittaker et al. reported data that according to our calculation showed participants' (a mix of students and workers) on-task times were around 60% of the total time, both with and without the tool (the tool reduced the overall total time) (Whittaker et al., 2016). A methodological thorough study of social media use among university students by (Y. Wang & Mark, 2018) found that 25% of the students' Facebook use occurred after schoolwork activities (other use occurred during leisure activities), no matter if they were frequent users or not; unfortunately the authors did not report time use on Facebook part of total time on learning activities. A relevant non-HCI study by Leysen et al. (2016) of 194 undergraduate students at a South African university cited a Computers & Education study by Fried (2008) in which users reported that they multitasked (did things other than take lecture notes) for an average of 17 min out of each 75 min class period, that is, a quarter of the lecture period engaging with digital media unrelated to the subject being taught. Of the students who reported their laptop uses during lectures 81% reported that they checked email during the lectures, 68% reported that they used instant messaging, 43% reported surfing the net, 25% reported playing games, and 35% reported doing "other" activities. Leysen et al. (2016) found themselves in their own study that 19% of university students reported that they were messaging constantly during lectures and 10% reported that they were constantly on social media during lectures. Since it is probably not the case that university students do media multitasking constantly during lectures etc., there is a need for more precise user studies on university students' media multitasking over time of online lectures, to feed HCI design.

Therefore, in the rest of this section, we review the general literature on media multitasking behaviour against the two dimensions of WHAT and HOW in HCIoT model. The WHAT categories that describe the phenomenon that we study. The HCIoT models has four subcategories of WHAT dimension: Human, Computer, Interaction, over Time. As for the subcategory of *human*, gratifications derived from media multitasking reveal important personal dispositions that drive behaviours of engaging in multiple media synchronically or sequentially (Hwang, Kim, & Jeong, 2014; Z. Wang & Tchernev, 2012; Zhang & Zhang, 2012).

In terms of the subcategory of *computer*, growing evidence has shown that media multitasking behaviour could also be related to technology/media factors' fundamental ordering of the temporalities of digital life. In particular, the smartphones' extension of the user's body and determination of identity and way of being has been named, negatively, as no-mobile-phone-phobia, or 'nomophobia' (Anshari, Alas, & Sulaiman, 2019; Kononova & Chiang, 2015; Rodríguez-García, Moreno-Guerrero, & Lopez Belmonte, 2020). Thus, today's 'nomophobic designs' [our term] of smartphones are directly outcomes linked to the basic computer qualities such as ease of use, speed, useful, efficient, convenient, portable, easily accessible that induce certain behaviours in humans (Busch & McCarthy, 2021). With the increasing intelligence and speedy adaptivity of the designs, the temporal ordering effects of these computer qualities is becoming ever more visible.

The *interaction* subcategory of the HCIoT model points to the pace of human-computer synchronization. It includes how humans are slower that the ever-faster computers, and how work with computers such as remote work and online learning impacts distribution of work hours and leisure hours (something very characteristic of the Covid-19 period). Thus, the interaction between the empirical factors captured by the other subcategories of the WHAT dimension in HCIoT (i.e., Human, Computer, over Time) may be more predictive and useful in predicting media multitasking behaviour than any single factor. However, the role of the interaction between these different factors in predicting media multitasking behaviour is not fully supported by empirical research. How these different factors may operate mutually in shaping the media multitasking behaviour remains unknown (Grove, 2020; König & Waller, 2010; Magen, 2017; Zhang & Zhang, 2012). Thus, the extant literature on media multitasking not only explores explanations about what factors that shape media multitasking behaviour but have also endeavoured to reveal how different factors may work independently or mutually in predicting media multitasking behaviour. A single factor-centric approach represented by classical Uses and Gratifications Theory (UGT) would imply that personal needs and motives for media multitasking (MMM) work independently in predicting media multitasking behaviour sequentially (Hwang et al., 2014; Z. Wang & Tchernev, 2012; Zhang & Zhang, 2012). By contrast, several theories, including situated action theory (Zhang & Zhang, 2012)), person-environment fit model (König et al., 2010), and media and audience factors (Jeong & Fishbein, 2007; Yang & Zhu, 2016), suggest a mutual (combinatory) approach. Human aspects (i.e., gratifications derived from media multitasking) alone are inadequate to explain media multitasking behaviour in real life, which is fluid and flexible in nature. Instead, the interaction between different factors (i.e., human, technology, and environment) may be more predictive and useful.

Finally, the subcategory of *over Time* is the defining aspect of the HCIoT model (Wiberg & Stolterman, 2021) and we approached this issue by looking at the frequency of recurring media multitasking behaviour and changes over two weeks during the Covid-19 pandemic. The current literature indicates that the environment, understood as situation and other context factors, may explain the reasons for adopting multitasking as the way of organizing our life around the use of media/technology (Green, 2014; König et al., 2010; Magen, 2017; Zhang & Zhang, 2012). Specifically, the HCIoT model suggests that the larger temporal environment in terms of phases, waves, periods, etc. provides a determining context that defines the scope and focus of the HCI phenomena. Thus, the HCIoT model helps to explore the Covid-19 period as a temporal context for HCI phenomena.

As to the HOW dimension of the HCIoT model, how data collection and analysis can be conducted with a temporality lens remains an open question (Wiberg & Stolterman, 2021). Existing literature on media multitasking behaviour in real life is based mainly on evidence from self-report measures (but see (Lyngs et al., 2020) study of Facebook use for a triangulation of subjective self-report and objective measurement). Given the evidence that 'existing self-report instruments are unlikely to be sensitive enough to accurately predict basic technology use related behaviours' (Ellis et al., 2019, p.86), both self-report and objective behavioural measures of media multitasking in online courses were assessed in the present study to discover possible differences. Collection of self-report measures and objective behavioural measures may help approach different aspects of media multitasking behaviour during an online course through a temporal lens.

In the next sub-sections, we will present our hypotheses based on what is known about media multitasking behaviour in relation to the subcategories of the WHAT and HOW dimensions in HCIoT model.

2.1 Human motives and media multitasking behaviour

Uses and Gratifications Theory (UGT) offers a classic approach to explore the role of human part of the WHAT dimension in media multitasking behaviour in online courses during Covid-19. In existing literature, media multitasking behaviour has been approached extensively from the human motives for doing several things synchronically or sequentially. According to UGT, human are conscious of their needs for pace and rhythm of life and are active in choosing and using media to fulfil them (Ha, Kim, Libaque-Saenz, Chang, & Park, 2015; Li, Liu, Xu, Heikkilä, & Van Der Heijden, 2015; Zhang & Zhang, 2012), something which the relative isolation of humans during Covid-19 may draw out. Prior literature supporting UGT has demonstrated that gratifications derived from media multitasking fulfil various needs and are thus important personal motives that shape media multitasking behaviour (Hwang et al., 2014; Zhang & Zhang, 2012). For instance, a motive for efficiency can drive humans to engage in media multitasking because they believe media multitasking is an effective way of learning information and results in cognitive gain. Literature based on UGT has identified four general categories of media multitasking-related motives: cognitive (e.g., seeking information and efficiency), emotional (e.g., relaxation, enjoyment and killing time), social (e.g., connection using Facebook during a class; again, Covid-19 isolation probably has made this need motive more important), and habitual (e.g., addiction and need for background noise)(Hwang et al., 2014; Kononova & Chiang, 2015; Z. Wang & Tchernev, 2012). The four categories of media multitasking-related motives support the argument of Pschetz (2015) that "people's use of this technology is […] complex and should not be reduced to efficiency and discipline".

The relationship between human motives and media multitasking is medium-dependent and content-dependent. For instance, the information motive predicted both mobile-based and Internet-based multitasking, but did not predict TV-based multitasking (Hwang et al., 2014). The role of motives for media multitasking (MMM) in predicting media multitasking behaviour in online courses thus remains unclear. Given the pervasiveness of media multitasking behaviour in students, this paper posits that the MMM explanations that are relevant to other media may also apply to explaining media multitasking behaviour in online courses. First, previous research found that information seeking acted as a motive for Internet-based multitasking to gain more information (Hwang et al., 2014; Z. Wang & Tchernev, 2012) and for TV-based multitasking to search for a particular product when an advertisement for the product was shown on TV (Zigmond & Stipp, 2010). Taking an online course is based on an Internet connection, and knowledge that is new to students is usually introduced in an online course, both of which may drive students to seek information related to the new knowledge on the Internet. Second, prior research found that convenience and efficiency gratifications (e.g., saving time, multitasking is convenient) predicted general, multiple media, and work-related computer multitasking (Hwang et al., 2014; Zhang & Zhang, 2012). However, the power of efficiency in predicting media multitasking measured using the media multitasking index (MMI) has not been replicated in another study (Kononova & Chiang, 2015). We posited that students may choose to multitask when they believe that multitasking during an online course is an efficient way of learning. Third, social motives (e.g., to maintain interpersonal relationships, checking messages from others) may also drive students to engage in social-related multitasking while taking online courses. Social gratification was found to be a predictor of multitasking when exposed to advertising (Hwang et al., 2014). Judd (2013) found that 165 out of 212 (78%) students used Facebook in at least one of the five sessions of computer-based self-directed learning, and considered Facebook use a key contributor to college students' task switching and multitasking behaviours. Another study found that engaging in social activities (e.g., chatting with one's neighbours and using Facebook) was the most frequent multitasking activity among students. However, the power of social gratification in predicting media multitasking was not replicated in the study by Wang and Tchernev (2012). Fourth, media multitasking can be driven by emotional gratification. For instance, those who believe that multitasking is fun or enjoyable, or that a single medium is boring were more likely to engage in Internet-based multitasking (Hwang et al., 2014). Wang and Tchernev (2012) found that emotional needs were gratified by media multitasking while cognitive needs were not. However, the power of enjoyment/entertainment in predicting media multitasking was not replicated in the study by Kononova and Chiang (2015), in which emotional gratification did not predict media multitasking. Therefore, emotional gratification derived from media multitasking may implicitly drive students to engage in media multitasking. Finally, dynamic UGT asserts that the impact of individual needs, gratifications, and media multitasking are reciprocal and self-reinforcing. As a result, habitual needs and gratifications increased media multitasking (Z. Wang & Tchernev, 2012). Hwang et al. (2014) found that habit motives predicted general media multitasking, not medium-specific or content-specific multitasking. Previous media multitasking experience may also reinforce the behaviour by accumulating the influences of needs and gratifications. The habitual motive is thus a potential driver of media multitasking behaviour in online courses for those who used to engage in media multitasking in classrooms.

In sum, the existing literature on the human aspect of WHAT dimension of media multitasking behaviour seen through a temporality lens has moved beyond time optimization (i.e., efficiency), which is one of the focuses of the first wave of time and temporality studies in HCI (Wiberg & Stolterman, 2021), and explored other aspects. This strand of research also resonates with the emerging themes in the second- and third-wave of HCI such as participation and shared interaction (social motives) (Bødker, 2015), slow design and slow technology (enjoyment motives) (Pschetz, 2015), and deep time design thinking (habitual motives) (Rahm-Skågeby & Rahm, 2021).

Despite the literature supporting the significance of MMM in media multitasking behaviour, it also shows that the relationship between personal motives and media multitasking behaviour is medium-dependent and varies with different categories of motives (Hwang et al., 2014; Kononova & Chiang, 2015; Zhang & Zhang, 2012). The role of different MMM in predicting media multitasking behaviour in online courses during Covid-19 remains an open question. Evidence has also shown that the association of human motives with self-report measures of media multitasking disappears with performance indicators of media multitasking (König, Bühner, & Mürling, 2005). Psychological traits were only found to be weakly or not associated with objective behavioural measures of technology usage in existing literature (Ellis et al., 2019; Rozgonjuk, Levine, Hall, & Elhai, 2018).

Based on the literature as mentioned above, together with a hunch that Covid-19 human isolation would draw out personal dispositions for multitasking, we developed the following hypotheses regarding the role of MMM in predicting media multitasking behaviour in online courses during Covid-19:

- Hypothesis 1-1: MMM can predict self-report media multitasking behaviour in an online course during Covid-19.
- Hypothesis 1-2: MMM cannot predict the objective behavioural measures of media multitasking in an online course during Covid-19.
- Hypothesis 1-3: The predicting power of MMM during an online course varies depending on the type of motive during Covid-19.

2.2 Computers and media multitasking behaviour

Computers encourage multitasking in human behaviour (Spink, Cole, & Waller, 2008; Zhang & Zhang, 2012), and during Covid-19 computers were even more important and necessary in many peoples' life than before. The prevalence of media devices (e.g., mobile phones, also called smartphones) among students increases their engagement in media multitasking behaviour (Kononova & Chiang, 2015). Dynamic UGT extends the classical UGT by highlighting the influence of past media multitasking experience on self-reinforcing needs and gratifications. For example, students' previous experiences of interacting with computers may reinforce or change their later behaviour (Z. Wang & Tchernev, 2012). The presence of mobile phones and addiction to media is positively associated with multitasking in online and face-to-face courses, due to the students' attachment to mobile phones as a result of their frequent interaction with mobile phones (Lepp et al., 2019; Mendoza, Pody, Lee, Kim, & McDonough, 2018). The term nomophobia (NP), or no-mobile-phone-phobia, was coined to describe the 'fear of being out of mobile phone contact' (Securenvoy, 2012) and also the "discomfort or anxiety caused by the non-availability of an mobile phone, PC or any other virtual communication device in individuals who use them habitually" (King et al., 2013, p. 140). Thus, mobile phones are not only enablers of media multitasking behaviour, they are also inducers of media multitasking behaviour (Benbunan-Fich et al., 2011). The intelligent and adaptive design qualities of mobile phones that make them appear indispensable to most humans, provide possibly a strong effect on media multitasking, which is currently best captured by measuring NP. In this sense, NP is mainly a general computer design issue – a 'nomophobic design' - and not a disorder in the person. Current theories of media multitasking indicate that anxiety or fear in response to being separated from one's mobile phone is an ubiquitous phenomenon because of the pervasiveness and vitalness of mobile phones in modern life and the reliance on mobile phones developed over time (Trub & Barbot, 2016). In particular, trait anxiety is positively associated with self-report media multitasking (Seddon, Law, Adams, & Simmons, 2018). Although anxiety resulting from NP was also associated with frequency of media use (e.g., Facebook) (Hart, Nailling, Bizer, & Collins, 2015; Mendoza et al., 2018; Oldmeadow, Quinn, & Kowert, 2013), its association with media multitasking behaviour in online courses is not clear. In a study deploying a qualitative approach, young undergraduate students reporting NP also reported that they could multitask very well (Anshari et al., 2019), probably because of the partly computer-determined nature of NP.

The multifunctionality of mobile phones has increased the number and types of activities in which we can engage with mobile phones and thus has enhanced the likelihood of multitasking with mobile phones. Consequently, mobile phones are currently used as a common medium of multitasking. The technology and design behind mobile phones may strengthen and amplify the ability of performing multiple tasks at the same time and result in overconfidence believing that it is easy to multitask. Current university students are thus likely to rely on mobile phones to satisfy their needs of multitasking while taking online courses. Hence, university students with NP either use a mobile phone to ease anxiety caused by NP or rely on a mobile phone to multitask when needed. NP is, therefore, likely to explain variance in online learning multitasking behaviour. However, in line with predictions grounded in mutual approach, we propose the following hypotheses:

- Hypothesis 2-1: NP can predict media multitasking behaviour in an online course during Covid-19.
- Hypothesis 2-2: NP cannot predict the objective behavioural measures of media multitasking in an online course during Covid-19.

2.3 Over time environmental demands and media multitasking behaviour

The over Time subcategory of the WHAT dimension in the HCIoT model suggests that the larger temporal context such as the situational/environmental demands during the Covid-19 period is important for the understanding of HCI phenomena. Consequently, Covid-19-typical *over time* environmental demands on media multitasking (ED) may drive media multitasking behaviour. During pre-Covid off-line university courses students took courses together in shared physical environments (e.g., the same classroom with same information technologies supporting their learning), social environments (e.g., same peer students during same course and are rarely distracted by surrounding people), and same indoors and outdoors conditions that may impact the effectiveness of taking courses. In contrast, during Covid-19 students were isolated and participated in online learning at their own home where both the physical and social environments, indoors and outdoors, were different from one student to another. This implies that the Covid-19 period can be studied broadly as a temporal context that provides various everyday environmental stimuli that shapes students' media multitasking in online courses. Thus, besides human motivation (HCIoT subcategory 1) and computer designs (HCIoT subcategory 2), there may be an overall effect of the larger Covid-19 context providing distracting environmental stimuli that lead to increased media multitasking. For example, it could be the Covid-19 determined social environment such as family relatives regularly calling for care because the student is online but at home and available (i.e., the work/family demands (König et al., 2010)), or other environmental stimuli in the home setting such as daily delivery of goods at the front door, or the washing machine finishes with noisy and distracting beeps (Lee et al., 2022), etc. This may lead to the student engage in other activities during participation in the university course, something perhaps quite characteristic of Covid-19 period.

Environment-dependent time-awareness plays an important role in our lives (Pschetz, 2015). The multitasking demands of contemporary work and learning environments calls for a use of the environment factor to explain human behaviour (Clemmensen, Kaptelinin, & Nardi, 2016; Diamond, 2013; König & Waller, 2010; Rahwan et al., 2019; Zhang & Zhang, 2012). In the case of online learning, lack of connectedness and instructor presence are associated with student disengagement (Bowers & Kumar, 2015). Hence, the method of interacting with an environment may make a difference for media multitasking during an online course. On one hand, being aware of the task-related environmental stimuli and making a decision about the strategy to deal with the stimuli are essential for the success of media multitasking in an environment that demands multitasking (Himi, Bühner, Schwaighofer, Klapetek, & Hilbert, 2019); coping efficiently with multiple streams of information is likely essential for the success of completing tasks in an online course. On the other hand, a laboratory study found that heavy media multitaskers are more distracted by irrelevant stimuli than light media multitaskers because heavy media multitaskers tend to allow irrelevant stimuli into working memory even though they are less efficient at switching tasks (Z. Wang & Tchernev, 2012). The detrimental consequences of media multitasking behaviour are partly associated with the misallocation of attention to environmental stimuli and the failure of controlling responses to irrelevant stimuli and tasks (Eysenck, Derakshan, Santos, & Calvo, 2007; Ophir, Nass, & Wagner, 2009; Ralph, Thomson, Cheyne, & Smilek, 2014).

Consequently, ED may drive media multitasking behaviour. According to dynamic UGT, the context of media behaviour is dynamically changed by the interaction between users and environment. The extent to which gratifications are obtained from the dynamic context can exert influence on subsequent behaviour (Z. Wang & Tchernev, 2012). ED makes a difference in media multitasking during an online course together with human and computer aspects. In line with the differences between self-report and objective behavioural indicators, we proposed the following hypotheses with respect to the role of ED in media multitasking during an online course:

- Hypothesis 3-1: ED can significantly improve the prediction of self-report measures of media multitasking in an online course during Covid-19.
- Hypothesis 3-2: ED cannot predict the objective behavioural measures of media multitasking in an online course during Covid-19.

2.4 Interaction and media multitasking behaviour

The mutual approach of media multitasking argues that human aspects (i.e., gratifications derived from media multitasking) alone are inadequate to explain media multitasking behaviour in real life, and instead proposes that the interaction between different factors (i.e., human, technology, and environment) may be more predictive and useful. People's media multitasking behaviour does not always follow their tendency preference, especially in situations where the multitasking demand is incongruent with their personal tendencies, motives, or preferences (Green, 2014; Lindquist & Kaufman-Scarborough, 2007; Magen, 2017; Z. Wang & Tchernev, 2012; Zhang & Zhang, 2012). For instance, job-related multitasking behaviour is determined by the extent to which the opportunity to work on multiple things at the same time during the work period matches with the person's preferences for multitasking (Hecht & Allen, 2005).

In line with the argument of HCIoT model that time and temporality are fundamental aspects of any interaction model, this paper attempts to investigate how human motives for media multitasking, computer capacity to induce/support media multitasking, and ED work together to account for the pace and rhythm of interaction during an online course. There are two approaches for how media multitasking behaviour is shaped: single factor-centric approach and a mutual approach. In contrast to the implied position of single factor-centric approach that human, computer and environment work independently to account for the pace and rhythm of interaction and thus determine the media multitasking behaviour (Hwang et al., 2014; Z. Wang & Tchernev, 2012; Zhang & Zhang, 2012), the mutual approach asserts that the pace of interaction and presence of a target behaviour not only requires human dispositions, such as sufficient motivation and ability to perform the behaviour, but also requires triggers for the behaviour either from technology or the situated environment (Fogg, 2009; König & Waller, 2010). Based on the reviewed studies and the person-environment fit argument in particular (Hecht & Allen, 2005; König & Waller, 2010), this study proposes a *human-computer-environment fit* index and argues that the media multitasking behaviour in online courses is mutually determined by three factors: human, computer and environment. Specifically, students with high motivation for media multitasking (see Section 2.1), high NP (see Section 2.2), and high ED (see Section 2.3) will engage in media multitasking more frequently and for longer periods. Low scores on any of the three independent factors will reduce the possibility of engaging in media multitasking in online courses. In this context, and given the fluid and flexible nature of media multitasking during an online course in everyday life (Zhang & Zhang, 2012), the current study assumed that a single factor is not powerful enough to predict the objective behaviour of media multitasking during an online course, especially when the predictors are measured using questionnaire-based self-report scales. Instead, this study argues that mutual theory, which places importance on the interplay between factors, may be more powerful in explaining media multitasking during an online course. This leads to the following hypothesis:

- Hypothesis 4: The human (MMM)-computer (NP)-environment (ED) fit can significantly enhance the prediction of both self-report and objective behavioural measures of media multitasking in an online course during Covid-19.

3. Method

3.1 Participants

Participants (N = 117; age mean [M] = 21.6, standard deviation [SD] = 2.06; male = 32, female = 84, self-report other = 1) for the survey study were recruited from three undergraduate and graduate online courses that took place over 9 weeks during March and April 2020 amid the COVID-19 outbreak. Participants were located in 25 different provincial areas when taking the online courses. Before participating in this study, all participants read a written consent form and those who consented to the study created their own unique research IDs without disclosing any personal information (e.g., not even initials were not permitted) to anyone else, including the researchers. This unique ID was later used at the time of completing the survey and sharing the logging data with the researcher, to help link the self-report data to logging data.

3.2 Measures of self-report variables

The courses were provided through an online platform known as téng xùn kè táng (腾讯课堂). The self-report measure of media multitasking used in this study included a survey that was administered immediately after taking two week's online courses. The three self-report predictor variables—MMM, NP, and ED—were measured using items from existing scales or adapted from previous literature.

Human factors (that is, MMM) were measured using a 20-item adapted version of the Multitasking Motives scale (Hwang et al., 2014). It included five sub-components of MMM in an online course: information (5 items; e.g., 'to seek additional information'), social (5 items; e.g., 'to express my opinion'), enjoyment (3 items; e.g., 'because multitasking is fun'), efficiency (4 items; e.g., 'to manage time efficiently'), and habit (3 items; e.g., 'because multitasking is a habit'). Cronbach's alpha values were .71–.88 for the subscales and .85 for the overall scale. Students responded to each item on a five-point Likert scale ranging from 1='not at all' to 5='very much'. Higher ratings reflected greater MMM in an online course.

The computer factor (that is, NP) was assessed using 20 items from the Nomophobia Questionnaire (Yildirim & Correia, 2015), which is composed of four dimensions, including (1) not being able to communicate (6 items; e.g., 'I would feel anxious because I could not instantly communicate with my family and/or friends'), (2) losing connectedness (5 items; e.g., 'I would feel anxious because I could not check my email messages,' (3) not being able to access information (4 items; e.g., 'I would feel uncomfortable without constant access to information through my smartphone'), and (4) giving up on convenience (5 items; e.g., Running out of battery on my smartphone would scare me'). Cronbach's alpha values were .73–.90 for subscales and .92 for the overall scale. Students responded to each item on a five-point Likert scale ranging from 1='not at all' to 5='very much.' Higher scores represented higher perceived anxiety caused by separation from mobile phones.

The environment factor was first probed by the extent to which the students' online learning course was affected by environment as a whole on a five-point Likert scale ranging from 1 = 'not at all' to 5 = 'very much'. Students then rated the influences of 5 environmental factors (e.g., outdoors noise, families, pets, household electrical devices, other) on their online learning course during Covid-19 on a five-point Likert scale ranging from 1 = 'not at all' to 5 = 'very much'. The low Cronbach's alpha value

(0.49) indicates that the 5 items of environmental factors had low internal consistency and were not closely related as a group. Therefore, the environmental factor (that is, ED) was hence measured as a whole using a single item (‘I have to engage in other activities when taking an online course’), which was inspired by a combination of items (e.g., ‘One has to hurry a lot to finish work here’, ‘I have too many family tasks to do’, ‘Family tasks put a heavy burden on me’, etc..) from the index of work/family demands (König et al., 2010) that says that higher work/family demands during work hours should be positively associated with the extent of multitasking behaviour. Students responded to the item on a five-point Likert scale ranging from 1 = ‘not at all’ to 5 = ‘very much’. Higher scores represent higher perceived environmental demands on media multitasking.

In addition, this study developed a human-computer-environment fit index (FI) based on the three above-mentioned self-report variables. The person-job fit model distinguishes between demands-abilities fit and supplies-values fit (Hecht & Allen, 2005). This study explored whether the environment and computer supplied opportunities to fulfil an individual’s value of media multitasking. The person-job fit model asserts that ‘when supplies and values are both high, such fit is associated with more positive reactions than when supplies and values are both low’ (Hecht & Allen, 2005, p. 157). In addition to the positive effect of fit, the person-job fit model also argues that a lack of fit is associated with lower levels of well-being (Hecht & Allen, 2005). These two models thus imply that both the sufficiency and fit of variables may affect the probability of media multitasking during an online course. Drawing on the methods that define fit in the extant literature, this study produced its own FI. This was determined by two contributors of the scores of the three human (MMM), computer (NP), and environment (ED) individual factors (the sufficiency contributor) and the differences between them (the fit contributor):

$$\mathrm{FI} = \mathrm{Sum}(\mathrm{MMM}, \mathrm{NP}, \mathrm{ED}) - |\Delta_{MMM-NP}| - |\Delta_{MMM-ED}| - |\Delta_{NP-ED}|.$$

The possible total scores of the FI can range from −1 to 15. The highest score of FI is 15 when the score of all three items is 5 (FI = Sum (5+5+5)−|5−5|−|5−5|−|5−5| = 15), and the lowest is −1 when one of the three individual factors has a score of 5 while the other two have a score of 1 (FI = Sum (5+1+1)−|5−1|−|5−1|−|1−1| = −1). Thus, a user who has a high level of MMM, NP, and ED simultaneously is most likely to engage in multitasking intensely. Any discrepancies between these factors will reduce the possibility of media multitasking. Since the current study hypothesized that the predicting power of media multitasking during an online course will vary depending on the type of motive (Hypothesis 1–3), accordingly, five types of FI were measured including information motive FI, social motive FI, efficiency motive FI, enjoyment motive FI, and habit motive FI.

Further, among the four measures of media multitasking during an online course (dependent variables), two were measured with self-report indicators. The first self-report indicator, the media multitasking index (MMI) for online courses, was inspired by and adapted from the Media Use Questionnaire developed by Ophir et al. (2009) . In the study by Ophir et al. (2009), participants reported their total number of hours per week spent using 12 different forms of media, such as reading print media or digital materials (e.g., newspapers, magazines, books), playing video or computer games, etc. In the present study, we measured the total number of minutes spent in an online course, which was 190 minutes (four 45-minute classes plus two intervals), and participants indicated the extent to which they used other forms of media (FOM) while taking the online course by responding with ‘Most of the time,’ ‘Some of the time,’ ‘A little of the time,’ or ‘Never.’ Thus, the media multitasking index for online courses (Ophir et al., 2009) was derived from the aforementioned two types of responses (i.e. number of hours per week spent using 12 different forms of media and the extent to which other forms of media were used while using one of the 12 media) to the Media Use Questionnaire using the following formula:

$$MMI = \sum_{i=1}^{i=11} \frac{m_{oc} \times h_{OC}}{h_{total}},$$

where h_{total} is the total number of minutes spent on all media, h_{oc} is the number of minutes spent in the online course, and m_{oc} is derived from the students’ self-reported extent to which they engage in other forms of media during an online course. In this study, we were only concerned about the media multitasking during the online course, so h_{total} equals h_{oc}. Numeric values were assigned to students’ self-report extent as follows: 1 was assigned to ‘Most of the time,’ 0.67 to ‘Some of the time,’ 0.33 to ‘A little of the time,’ and 0 to ‘Never.’ The resulting media multitasking index value indicates the extent of media multitasking for 11 forms of media during an online course.

The second self-report indicator, media multitasking percent (MMP), was inspired by previous literature (Hwang et al., 2014) and measured using the percentage of time spent engaging in other activities while taking an online course in the past one week (e.g., ‘Of the total amount of time you spent in online courses in the past one week, how often did you multitask? Please estimate the percentage of time with a number from 0 to 100’). While MMI indicates the extent of media multitasking, MMP reflects the overall proportion of time spent during an online course.

3.3 Measures of objective behavioural variables

After completing the self-report survey, forty students volunteered to install an experience sampling tool (an Android-based experience sampling tool that we developed for a series of studies) on their personal mobile phone to facilitate collection of their objective behaviour of using all types of media over the past two weeks (i.e., usageStatsManager.queryEvents), through the click of a button in the experience sampling tool. The usage events (see Table 1) of the past two weeks were written into the internal storage and sent to the researcher via e-mail if students consented to the study. The measures of objective behavioural variables were analysed based on the logging data of four 45-minute classes plus two 5-minute intervals, during which the teacher took questions.

Table 1 The logging data and events collected in this study

Logging Data	Logging Events
Media Name	getPackageName
Media Event	UsageEvents.Event.MOVE_TO_FOREGROUND
	UsageEvents.Event.MOVE_TO_BACKROUND
Event Time	getTimeStamp

Although the mobile application for téng xùn kè táng, for Android or iOS users, was available on its official site (https://ke.qq.com/), students were encouraged to install and use the software to take the online course on their computers because of the convenience and ease of using a bigger screen for displaying course content. However, the data showed that five students used the mobile application of téng xùn kè táng during the online course. Students reported a range of reasons for using the mobile application, including ‘checking messages in the chat room of téng xùn kè táng becomes possible,’ ‘interacting with the teacher or classmates is more convenient,’ and ‘for searching information,’ etc. As a result, using both téng xùn kè táng and other applications/media on mobile phones were considered media multitasking behaviour.

Ellis et al. (2019) indicated that allowing students to view their own usage data in real-time may bias the correlation between self-report measures and objective measure of behaviour (p. 91). Accordingly, the students in this study were informed of what data would be collected but they were unable to view the summary of their own usage data in real-time (e.g., the total amount of time spent on their mobile phone) before filling the survey and the logging data created by the experience sampling tool only showed the package name (e.g., com.tencent.mm) and related timestamp (e.g., Moving-to-Foreground: 2020/03/29 17:40).

In an attempt to compare the self-report and objective behavioural measures of media multitasking, and informed by the two indicators of self-report measures of media multitasking (MMI and MMP), two objective measures of media multitasking were used in the present study. In line with the number of hours per week spent using 12 different forms of media in self-report measures, the first objective behavioural variable of media multitasking during an online course was hence calculated by the overall running time of all media on the foreground of the participant’s mobile phone during the four 45-minute online classes (i.e., time spent on media multitasking, TMM) plus two 5-minute intervals. Similarly, in line with the extent to which other forms of media were used while using one of the 12 media in self-report measures, the second objective behavioural variable of media multitasking in the online course was calculated on the basis of the frequency of use of different forms of media on the foreground of the participant’s mobile phone (i.e., forms of media index, FOM).

3.4 Data analysis

The survey data combined with data from the experience sampling tool were screened for anomalies and then analysed using SPSS Version 23 (SPSS, Inc, Chicago, IL, USA). Descriptive statistics were first used to calculate the mean (M), standard deviation (SD), maximum value (Max.), and minimum value (Min.) of independent and dependent variables, followed by tests for statistical significance and effect size to examine the magnitude of differences of means between independent and dependent variables and whether the differences were due to random chance. Second, Pearson’s correlation was calculated for the objective behavioural measures during the two weeks to test the fluid and flexible nature of objective behavioural measures of media multitasking during an online course.

Finally, hierarchical linear regressions were conducted to examine the role of independent variables (i.e., MMM, NP, and ED) in predicting the measures of media multitasking. The assumptions of multicollinearity based on the values for tolerance and the variation inflation factor were examined and were above .10 and below 10, respectively, for all models (See Table 2). For each of the four indicators of media multitasking, in Step 1, we entered one of the five MMMs as a predictor. In Step 2, NP and ED were entered to investigate whether they predicted media multitasking during an online course better than either of the five motives individually (measured by improvement in the proportion of explained variance, ΔR^2). In Step 3, fit (FI) of one of the five MMMs, NP, and ED were entered to see whether human-computer-environment fit can significantly improve the prediction of media multitasking during an online course over their independent power.

Table 2. Tolerance and the variation inflation factor of predictors of self-report and objective behavioural variables

		TE	VIF		TE	VIF		TE	VIF		TE	VIF		TE	VIF
Self-report	IN	0.98	1.02	SL	0.54	1.84	EY	0.44	2.25	ET	0.42	2.37	HT	0.53	1.89
	NP	0.69	1.45	NP	0.88	1.13	NP	0.96	1.04	NP	0.90	1.12	NP	0.90	1.11
	ED	0.27	3.71	ED	0.51	1.95	ED	0.39	2.54	ED	0.68	1.46	ED	0.64	1.55
	FI_IN	0.23	4.41	FI_SL	0.35	2.84	FI_EY	0.26	4.26	FI_ET	0.36	2.81	FI_HT	0.39	2.57
Objective behavioural	IN	0.95	1.05	SL	0.45	2.21	EY	0.50	2.02	ET	0.67	1.50	HT	0.43	2.35
	NP	0.77	1.29	NP	0.91	1.10	NP	0.98	1.03	NP	0.95	1.05	NP	0.99	1.02
	ED	0.13	7.66	ED	0.31	3.26	ED	0.34	2.91	ED	0.56	1.78	ED	0.48	2.08
	FI_IN	0.12	8.29	FI_SL	0.20	4.97	FI_EY	0.22	4.48	FI_ET	0.42	2.38	FI_HT	0.26	3.92

Notes. IN= information motive for media multitasking; SL = social motive for media multitasking; EY = efficiency motive for media multitasking; ET = enjoyment motive for media multitasking; HT = habit motive for media multitasking; NP = nomophobia; ED = environmental demands on media multitasking; FI_IN= information motive FI; FI_SL = social motive FI; FI _EY = efficiency motive FI; FI_ET = enjoyment motive FI; FI_HT = habit motive FI; TE=tolerance; VIF = variation inflation factor.

4. Results

4.1 Descriptive analysis and test for differences of means

As shown in Table 3, among the five MMMs in an online course during Covid-19, the average level of information motive (M = 3.6, SD = 0.7) was significantly higher than that of efficiency motive (M = 2.6, SD = 1.1, $t(116) = 9.8$, $p < .01$, $d = 1.20$), enjoyment motive (M = 2.4, SD = 1.1, $t(116) = 10.34$, $p < .01$, $d = 1.33$), habit motive (M = 2.5, SD = 1.0, $t(116) = 10.07$, $p < .01$, $d = 1.31$), and social motive (M = 2.8, SD = 0.9, $t(116) = 9.15$, $p < .01$, $d = 1.05$). Information motive was also the only motive that was significantly above the neutral level of 3 ($t(116) = 9.99$, $p < .01$, $d = 0.93$). The average level of NP and ED were 3.2 (SD = 0.8) and 2.3 (SD = 1.1) respectively. Similarly, among the five FIs, the level of information motive FI (FI_IN) (M = 5.4) was also significantly higher than the efficiency motive FI (FI_EY) (M = 4.8, SD = 2.5, $t(116) = 4.0$, $p < .01$, $d = .24$), the enjoyment motive FI (FI_ET) (M = 4.3, SD = 2.3, $t(116) = 5.6$, $p < .01$, $d = .45$), the habit motive FI (FI_HT) (M = 4.5, SD = 2.4, $t(116) = 4.7$, $p < .01$, $d = .36$), and the social motive FI (FI_SL) (M = 5.0, $t(116) = 2.9$, $p < .01$, $d = .16$).

Table 3. Self-report and objective behavioural variables

Variables	Measures	M	SD	Max.	Min.
	Self-report				
	IN	3.6(3.7)	0.7(0.8)	5(5)	1.4(1.4)
	EY	2.6(2.6)	1.1(1.0)	5(4.8)	1(1)
	ET	2.4(2.7)	1.1(1.1)	5(5)	1(1)
	HT	2.5(2.7)	1.0(0.9)	5(4.7)	1(1)
	SL	2.8(3.1)	0.9(0.9)	5(5)	1(1)
Independent	NP	3.2(3.4)	0.8(0.7)	5(5)	1.3(1.8)
	ED	2.3(2.3)	1.1(1.0)	5(5)	1(1)
	FI_IN	5.4(5.6)	2.6(2.5)	11.7(11.7)	-0.4(0.9)
	FI_EY	4.8(4.8)	2.5(2.5)	11.3(10.9)	-0.7(0.3)
	FI_ET	4.3(4.8)	2.3(2.4)	12(9.7)	-1.0(-1.0)
	FI_HT	4.5(5.0)	2.4(2.4)	12(11)	-0.7(0.4)
	FI_SL	5.0(5.5)	2.3(2.5)	11.4(11.4)	0.1(0.5)
	Self-report				
	MMI	1.7(2.2)	1.2(1.5)	6.3(6.3)	0(0.3)
Dependent	MMP	25%(26%)	18%(14%)	100%(60%)	2%(0%)
	Objective behavioural				
	FOM	9.2	4.2	23	2
	TMM	1134	1744	7763	0

Notes. Values in parentheses are based on the data of 40 students who participated in the logging study. IN= information motive for media multitasking; SL = social motive for media multitasking; EY = efficiency motive for media multitasking; ET = enjoyment motive for media multitasking; HT = habit motive for media multitasking; NP = nomophobia; ED = environmental demands on media multitasking; FI = fit index; FI_IN= information motive FI; FI_EY = efficiency motive FI; FI_ET = enjoyment motive FI; FI_HT = habit motive FI; FI_SL = social motive FI; MMI media multitasking index; MMP = media multitasking percent; TMM= time spent on media multitasking; FOM= forms of media.

The environment played a significant role in the online courses during Covid-19 (M = 3.37, SD = 1.2, $t = 3.33$, $p < .01$, compared to 1 = 'not at all'). All the five environmental factors (e.g., outdoors noise, families, pets, electrical devices, other) made a difference to students' online learning course during Covid-19 (compared to 1 = 'not at all'). As expected, students reported various environmental situations in which they had to multitask when taking online courses during Covid-19, such as climbing up to the top of the nearby mountain to get better telecommunication network, finding it inconvenient to join the discussion section because of having to taking care of the cows, failing to respond to questions due to using the washroom, or taking care of grandparents or little siblings.

Regarding the dependent variables, the value of MMI indicated that the overall time students spent on media multitasking was 1.7 times of the time spent in the online course. The MMP findings suggested that, on average, 25% of the time was spent engaging in other activities while taking part in the online course. The difference between MMI and MMP indicated that media multitasking was higher when it was rated separately on different forms of media than when it was rated as a whole. Additionally, one of the objective behavioural measures of media multitasking during an online course, FOM, was 9.2 (Max=23, Min=2), which suggests that all students displayed media multitasking behaviour to some extent when taking an online course. Among all the media that students used during the online course, WeChat (a counterpart of Facebook and Facebook messenger) was used by the largest proportion of participants (95%, 38 out of 40), followed by Mobile QQ (70%, 28 out of 40, a counterpart of Facebook messenger) and Weibo (47.5%, 19 out of 40, a counterpart of Twitter). Although bigger-screen computers or tablets were recommended as the device for taking the online course, five students used the online course application on their mobile phones. The other objective behavioural measure, TMM, was 1134 seconds and accounted for about 10% of the total time of the four 45-minute classes plus two intervals (11400s). This was significantly lesser than the self-reported MMP (25%, $t(39) = -7.0$, $p < .01$, $d = 1.1$). The overestimation of the time spent on media multitasking reflects the well-established finding that the division of an interval into sub-intervals tends to increase its apparent duration (W. J. Matthews & Meck, 2014).

4.2 Objective behavioural measures of media multitasking over two weeks

The objective behavioural measures of media multitasking allowed us to capture and analyse the developments and change of media multitasking behaviour over time (Wiberg & Stolterman, 2021). Results showed no significant differences of FOM ($t(39) = .85$, $p > .05$, $M_{week1} = 6.1$, $M_{week2} = 6.0$) and TMM ($t(39) = .42$, $p > .05$, $M_{week1} = 520$, $M_{week2} = 614$) between two weeks, indicating that the media multitasking behaviour in terms of duration and forms of media during four 45-minute classes plus two intervals over two weeks are relatively stable on average.

However, the results of Pearson's correlation analysis showed that FOM during each of the two weeks were not significantly correlated ($r_{FOM} = .23$, $p > .05$) while TMM during each of the two weeks correlated significantly ($r_{TMM} = .72, p < .01$). Differences between the correlation coefficient values were examined (Meng, Rosenthal, & Rubin, 1992) and the results showed that the correlation of FOM during the two weeks was significantly lower than that of TMM ($z = 2.12$, $p < .05$). This result indicates that FOM is probably an indicator of the fluid aspect of media multitasking behaviour during an online course while TMM is relatively stable compared with FOM.

The data of FOM and TMM of two students was visualized to explore the pattern of media multitasking during an online course. Three types of media multitasking behaviour were observed depending on how students shift from online course to media and vice versa on mobile phone (see Figure 1). Direct shifting (DS) indicates shifting directly from online course to media on mobile phone and switching back to online course again after a certain period of time. Indirect shifting (IS) means first shifting from online course to a medium on mobile phone without switching back directly to online course after a certain period of time, instead shifting to another medium. Within-medium shifting (WS) means first shifting from online course to a medium on mobile phone without switching back directly to online course, instead then switching within that medium.

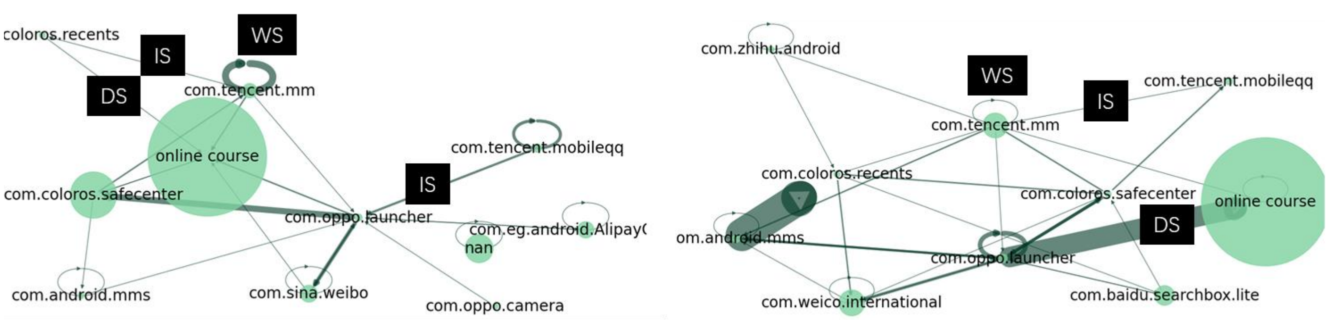

Figure 1. The media multitasking behaviour of two students during four 45-minute classes plus two intervals. Note: DS = Direct shifting; IS = Indirect shifting; WS = Within-medium shifting. The size of the node represents the time spent on each medium, and the weight of line represents the frequencies of shifting between media.

4.3 Predictors of media multitasking behaviours during an online course

As demonstrated by model 1 (M1; see Table 4) in which one of the five MMMs was entered as predictor of measures of media multitasking, MMI was significantly predicted by efficiency motive ($\beta = .32$, $p < .05$), enjoyment motive ($\beta = .26$, $p < .05$), and habit motive ($\beta = .19$, $p < .05$); MMP was significantly predicted by information motive ($\beta = -.19$, $p < .05$), efficiency motive ($\beta = .35$, $p < .01$), and enjoyment motive ($\beta = .30$, $p < .01$; Hypothesis 1-1 was supported). However, none of the motives significantly predicted the two objective behavioural measures of media multitasking (Hypothesis 1-2 was supported). Additionally, social motive did not predict any measures of media multitasking during an online course. Taken together, the results of M1 support Hypothesis 1-3 (see Table 5).

In model 2 (M2) of Table 4, in which NP and ED were entered to investigate whether they predicted media multitasking during an online course better than one of the five motives, the additional roles of NP and ED over one of the five MMMs during online course in predicting media multitasking during an online course were examined. The results showed that the additions of NP and ED not only significantly improved the prediction of MMI over information motive ($\Delta R^2 = .10$, $p < .01$, $f^2 = .11$), social motive ($\Delta R^2 = .10$, $p < .05$, $f^2 = .11$), enjoyment motive ($\Delta R^2 = .07$, $p < .05$, $f^2 = .07$), and habit motive ($\Delta R^2 = .08$, $p < .05$, $f^2 = .09$), but also the prediction of MMP over information motive ($\Delta R^2 = .14$, $p < .01$, $f^2 = .16$), social motive ($\Delta R^2 = .15$, $p < .01$, $f^2 = .19$), efficiency motive ($\Delta R^2 = .07$, $p < .05$, $f^2 = .09$), enjoyment motive ($\Delta R^2 = .10$, $p < .01$, $f^2 = .12$), and habit motive ($\Delta R^2 = .10$, $p < .10$, $f^2 = .12$). They also significantly improved the prediction of FOM over four subcomponents of motive (see Table 4; Hypothesis 2.1 and 3.1 were supported), and the effect sizes were between medium and large (.16-.22). In contrast, the prediction of TMM was not significantly improved with the addition of NP and ED.

Finally, the addition of FI (see M3 in Table 4) significantly enhanced the prediction of the MMI above and beyond enjoyment motive, NP, and ED ($\beta = .39$, $\Delta R^2 = .04$, $p < .05$, $f^2 = .05$), and habit motive alongside NP and ED ($\beta = .38$, $\Delta R^2 = .06$, $p < .05$, $f^2 = .07$); the prediction of MMP above and beyond information motive alongside NP and ED ($\beta = -0.37$; $\Delta R^2 = .03$, $p < .05$, $f^2 = .04$); and the prediction of FOM above and beyond information motive alongside NP and ED ($\beta = .94$; $\Delta R^2 = .13$, $p < .05$, $f^2 = .17$). Thus, Hypothesis 4 was supported.

Table 4. Hierarchical regression analysis of predictors of media multitasking behaviour during an online course

MMI																			
	M1	M2	M3		M1	M2	M3		M1	M2	M3		M1	M2	M3		M1	M2	M3
IN	.10	.11	.11	SL	.04	-.03	-.11	EY	.32*	.24*	.05	ET	.26*	.21*	.03	HT	.19*	.12	-.09
NP		.17	.17	NP		.19*	.18	NP		.15	.16	NP		.12	.12	NP		.15	.12
ED		.24*	.23	ED		.22*	.13	ED		.13	-.09	ED		.22*	.12	ED		.22*	.04
FI_IN			.01	FI_SL			.16	FI_EY			.39*	FI_ET			.27	FI_HT			.38**
R^2	.01	.11*	.11	R^2	.00	.10	.11	R^2	.10	.14	.18	R^2	.07	.14	.16	R^2	.03	.11	.17
ΔR^2	.01	.10	0	ΔR^2	.00	.10	.01	ΔR^2	.10**	.04	.04*	ΔR^2	.07*	.07*	.03	ΔR^2	.03*	.08**	.06**
f^2		0.11	0	f^2		0.11	0.01	f^2		.05	.05	f^2		.07	.07	f^2		.09	.07
MMP																			
	M1	M2	M3		M1	M2	M3		M1	M2	M3		M1	M2	M3		M1	M2	M3
IN	-.19*	-.18*	-.17*	SL	-.03	-.13	-.09	EY	.35**	.24*	.36**	ET	.30**	.24**	.39**	HT	.26	.18*	.15
NP		.26**	.38**	NP		.29**	.30**	NP		.22*	.22*	NP		.18	.18	NP		.20*	.20*
ED		.22**	.51**	ED		.24**	.30*	ED		.14	.28*	ED		.24*	.33**	ED		.23**	.20
FI_IN			-.37*	FI_SL			-.09	FI_EY			-.25	FI_ET			-.23	FI_HT			.06
R^2	.04	.17	.2	R^2	.001	.16	.16	R^2	.12	.19	.2	R^2	.09	.19	.21	R^2	.07	.17	.17
ΔR^2	.04	.14**	.03*	ΔR^2	.001	.15**	.01	ΔR^2	.12	.07*	.01	ΔR^2	.09**	.10**	.02	ΔR^2	.07	.10**	.00
		.16	.04	f^2		.19	0	f^2		.09	.01	f^2		.12	.03	f^2		.12	0
FOM																			
	M1	M2	M3		M1	M2	M3		M1	M2	M3		M1	M2	M3		M1	M2	M3
IN	.13	.14	.16	SL	.19	.07	-.23	EY	-.20	-.23	-.42	ET	.03	.07	-.02	HT	.25	.24	-.08
NP		.41**	.25	NP		.38*	.42**	NP		.38*	.40*	NP		.41**	.40*	NP		.40**	.37*
ED		.03	-.94**	ED		.03	-.40**	ED		.14	-.13	ED		.05	-.06	ED		-.02	-.30
FI_IN			.94**	FI_SL			.65*	FI_EY			.43	FI_ET			.18	FI_HT			.56
R^2	.02	.19	.31	R^2	.04	.17	.26	R^2	.04	.21	.26	R^2	.001	.17	.19	R^2	.06	.22	.30
ΔR^2	.02	.17*	.13*	ΔR^2	.04	.14	.09	ΔR^2	.04	.17*	.04	ΔR^2	.001	.17*	.01	ΔR^2	.06	.16*	.08
f^2		.23	.17	f^2		.16	.12	f^2		.22	.07	f^2		.20	.02	f^2		.21	.11
TMM																			
	M1	M2	M3		M1	M2	M3		M1	M2	M3		M1	M2	M3		M1	M2	M3
IN	-.02	-.02	-.02	SL	.15	.10	-.13	EY	-.15	-.17	-.30	ET	-.08	-.06	.08	HT	.21	.21	.06
NP		.22	.19	NP		.19	.22	NP		.20	.22	NP		.21	.25	NP		.21	.20
ED		.02	-.10	ED		-.01	-.34	ED		.09	-.10	ED		.03	.19	ED		-.04	-.17
FI_IN			.13	FI_SL			.51	FI_EY			.31	FI_ET			-.29	FI_HT			.27
R^2	0	.05	.05	R^2	.02	.06	.11	R^2	.02	.07	.09	R^2	.01	.05	.09	R^2	.04	.09	.11
ΔR^2	0	.05	.00	ΔR^2	.02	.03	.05	ΔR^2	.02	.05	.02	ΔR^2	.01	.05	.04	ΔR^2	.04	.05	.02
f^2		.05	0	f^2	.04	.06		f^2		.05	.02	f^2		.04	.04	f^2		.05	.02

Notes. $f^2 = .02$, small effect size; $f^2 = .15$, medium effect size; $f^2 = .35$, large effect size (Cohen, 1988, p. 407–414); MMI = media multitasking index; MMP = media multitasking percent; FOM= forms of media; TMM= time spent on media multitasking; IN= information motive for media multitasking; SL = social motive for media multitasking; EY = efficiency motive for media multitasking; ET = enjoyment motive for media multitasking; HT = habit motive for media multitasking; NP = nomophobia; ED = environmental demands on media multitasking; FI = fit index; FI_SL = social motive FI; EY_FI = efficiency motive FI; ET_FI = enjoyment motive FI; HT_FI = habit motive FI; M1= model 1 in which one of the five MMMs was entered as predictor of measures of media multitasking in step 1 of data analysis, M2= model 2 in which NP and ED were entered to investigate whether they improved the ability to predict media multitasking above and beyond one of the five motives in step 2 of data analysis, M3= model 3 in which fit of one of the five MMMs, NP, and ED were entered to investigate whether they improved the ability to predict media multitasking above and beyond their independent prediction in step 3 of data analysis

Table 5. Summary of the validation of the hypotheses

Hypothesis No.	Hypothesis	Result
Hypothesis 1-1	MMM can predict the self-report media multitasking behaviour in an online course during Covid-19.	Supported
Hypothesis 1-2	MMM cannot predict the objective behavioural measures of media multitasking in an online course during Covid-19.	Supported
Hypothesis 1-3	The predicting power of MMM in an online course during Covid-19 varies depending on the type of motive.	Supported
Hypothesis 2-1	NP can predict media multitasking behaviour in an online course during Covid-19.	Supported
Hypothesis 2-2	NP cannot predict the objective behaviour measures of media multitasking in an online course during Covid-19.	Not supported
Hypothesis 3-1	ED can significantly improve the prediction of self-report measures of media multitasking in an online course during Covid-19.	Supported
Hypothesis 3-2	ED cannot predict the objective behaviour measures of media multitasking in an online course during Covid-19.	Supported
Hypothesis 4	The human (MMM)-computer (NP)-environment (ED) fit can significantly enhance the prediction of both self-report and objective behavioural measures of media multitasking in an online course during Covid-19.	Supported

Note: MMM = Personal, human Motives for Media Multitasking; NP – NomoPhobia or 'nomophobic design' for media multitasking; ED = Environmental demands on media multitasking.

5. Discussion

This study used a HCI time and temporality lens to explore students' media multitasking behaviour in an online course during the COVID-19 period. For examples of such media multitasking see Figure 1. Specifically we explored the topic along the WHAT and HOW dimensions in HCIoT model that initially was proposed by Wiberg and Stolterman (Wiberg & Stolterman, 2021). We contribute to the first wave of time and temporality studies in HCI, which is characterized in part by studies of multitasking (Wiberg & Stolterman, 2021). This was done through investigating how students may deal with multiple media during an online course to optimize their time, and whether the four subcategories of the WHAT dimension in HCIoT model may explain the media multitasking behaviour during an online course. Secondly, we contribute to the second wave of time and temporality studies in HCI, which is characterized by a methodological attitude toward time and temporality and respond to the call for new approaches taken to the explicit study of time and temporality in HCI, through investigating HOW collection of both self-report and objective behaviour of media multitasking during an online course can provide different and holistic understandings of the temporal aspects of HCI. Thus we offer subjective measures to assess the perception of multitasking and typical multitasking habits in combination with behavioural measures, something which has been called for in HCI multitasking research (Benbunan-Fich et al., 2011; Lyngs et al., 2020). With this, we have also explored the Covid-19 period as a HCI time and temporality phenomenon, which may help open the next wave of HCI time and temporality studies. In the following, we first reflect on our findings in relation to the Covid-19 period as a new wave of HCI, and then discuss the specific hypotheses in the subsequent sections.

5.1 Pre-pandemic HCI compared to the Covid-19-period HCI

One way to reflect on our findings in relation to the Covid-19 period is to compare them with the pre-pandemic period. It turns out that student's media multitasking may be considerably less during the Covid-19 period. Our data from the Covid-19 period showed that university students were off-task time 25% (subjective) and 10% (objective) of total time (see section 4.1.), which indicates 75-90% on-task time of the total time during online lectures. In contrast, the much-cited pre-pandemic data by Rosen et al. (Rosen, Whaling, et al., 2013) indicated less on-task time of 70-72% of the total time, and the evaluation data by Whittaker et al. (Whittaker et al., 2016) showed participants' on-task times were around 60% of the total time, that is, much less on-task time than our data. Other pre-pandemic data by Leysen et al. (2016) indicated that many university students even do media multitasking constantly during lectures. Our data on students being 75-90% on-task in online lectures thus is a strong and surprising finding. When compared to the pre-pandemic period, the Covid-19 period HCI media multitasking appears as more serious and task-focused. Studying online during Covid-19 period do not allow much procrastination on social media or doing other activities than studying. However, the above pre-pandemic versus Covid-19 comparison is based on different groups of people, so the comparison is not solid enough. Generally, there is a need for more precise user studies on university students' media multitasking in online lectures during Covid-19-period conditions to help feed Covid-19 period HCI design. In the following we discuss our hypotheses results to help fill this gap.

5.2 Humans, computers and environment in media multitasking behaviour through a temporal lens

First, for the human subcategory of the WHAT dimension in HCIoT model, the results of this study showed that the motives and needs for engaging in multiple media (H1-1, see Table 5 for an overview of the hypotheses) made a difference to the students' media multitasking behaviour during the online course. This supports the widely adopted proposition by Uses and Gratifications Theory (UGT) that humans' needs or preferences alone are powerful enough to predict media multitasking behaviour (Hwang et al., 2014; Kononova & Chiang, 2015; Whiting & Williams, 2013). However, our results (H1-2) also indicate that the human subcategory of needs and motives may play its' significant role only for the self-report measures of time, not for the objective measures, which contrasts the UGT proposition. Furthermore, the prediction of efficiency, information, entertainment, and habit motives to media multitasking behaviour (H1-3) suggested that students' self-report media multitasking behaviour during online course was driven not only by gratifications derived from time optimization (i.e., efficiency) as expected from the first wave of time and temporality studies in HCI (Wiberg & Stolterman, 2021), but also derived from entertainment supported by having multiple devices (i.e., enjoying music on mobile phone while taking online course on computer) and the habit of engaging in multiple media, developed over time.

Second, the significance of the WHAT dimension's computer subcategory was confirmed by the results (H2-1) in the present study. The online course sampled in the present study was designed to be available on both computer and mobile phone, and the computer was recommended as the device of taking online course for its' bigger screen size than mobile phone. However, in our study the users (students) experiencing higher levels of nomophobic design of their mobile phone (NP) also experienced higher extent of media multitasking forms (MMI) and experienced more time spent on media multitasking (MMP). Contrary to our hypothesis (H2-2), this connection between NP and self-reported media multitasking also applied to the objective media multitasking behaviour during an online course. This result is not completely in agreement with previous literature, which has attributed the relationship between self-report smartphone usage scales and anxiety to their conceptual similarity (Ellis et al., 2019, p.91). As the wording of the media multitasking percentage ('Please specify the percentage of time using each of the following seven devices when taking an online course') is not conceptually like that of the nomophobia measure (e.g., 'I would feel uncomfortable without constant access to information through my smartphone'), there should be reasons other than conceptual similarity to explain their connection in the present study.

One alternative explanation is that the self-report measure of media multitasking was specified with the percent of time on specific devices rather than overall time of media multitasking, and the objective behavioural measure of media multitasking was calculated by the logging data of FOM and TMM on mobile phone. Similarly, the measures of NP in the present study were also very specifically about fear of being out of mobile phone contact. By contrast, neither human nor environmental factors specified the gratifications or demands derived from media multitasking with a mobile phone. This result not only echoes the argument that specific behaviours might be better mapped onto psychometric scales (Ellis et al., 2019), but also, more importantly, it demonstrates that the prevalence of mobile phones in modern life makes them an influential factor that likely either distracts students from focusing on ongoing task or facilitates users to fulfil the media multitasking tasks on demand (e.g., 'watching the livestream of course on a mobile phone or computer, taking notes on tablet'). Regarding the relative contribution of human motive and nomophobia, this study showed that NP significantly predicted some measures of media multitasking, while motives did not. The results indicate that the attachment to mobile phones and the resulting anxiety when being separated from mobile phones can override human dispositions in predicting media multitasking behaviour during an online course. The role of media ownership in predicting media multitasking behaviour has been demonstrated in existing literature (Cotten, Shank, & Anderson, 2014; Jeong & Fishbein, 2007). This present study extended the line of research by showing that the prevalence of mobile phones with multifunction and abundant media made ownership of a mobile phone a significant computer factor in predicting media multitasking behaviour (Lepp et al., 2019; Mendoza et al., 2018). For instance, students in the present study reported situations in which multitasking on a mobile phone facilitated their online course: 'It's more convenient to use the washroom with a mobile phone when taking an online course,' 'I have stored many materials on my mobile phone and it is more convenient to use the application on my mobile phone,' 'I used a mobile phone to check with my classmates about the situation on their side when the connection was unstable.' Nomophobia significantly predicted the variance in FOM while efficiency motive did not, which indicates that using a mobile phone for the purpose of efficiency/convenience when taking an online course was a subconscious behaviour.

Third, there is a growing agreement that demands of the environment variables (in our study: H3-1 and H3-2) may explain the inconsistency between human factors (e.g., preferences and motives for media multitasking) and objective behaviour/performance of media multitasking (Diamond, 2013; König et al., 2010; Magen, 2017; Zhang & Zhang, 2012). The significance of demands imposed in the online courses during the Covid-10 period was included in the present study. In the study of Zhang and Zhang (2012), the self-report frequency of using computers alone significantly predicted the amount of multitasking with multiple media sources ($\beta = .10$), and using computers when being with strangers significantly predicted the tendency to multitask for interaction purposes ($\beta = .14$). Based on the size of the regression coefficient (Min=.16, Max=.49), they concluded that 'situational factors have less powerful influence compared to gratifications' (Zhang & Zhang, 2012, p. 1883). In contrast, in our study ED significantly predicted the MMI (H3-1 and H3-2), which was not significantly predicted by information, social, or enjoyment motives. ED also predicted the MMP alongside information, enjoyment, and habit motives. Consequently, the environmental factor (Covid-19-typical *over time* environmental demands on media multitasking) was as influential, if not bigger than, motives in predicting self-report measures of media multitasking behaviour.

In sum, this study contributes to the studies of HCI through a temporal lens, by demonstrating the significance of the environment in explaining media multitasking behaviour in an online course during the Covid-19-period. Furthermore, our results indicate that the human factor (i.e., MMM), computer factor (i.e., NP), and environmental factor (i.e., ED) all play their unique role in explaining media multitasking behaviour.

5.3 Interaction between human, computer and environmental factors in media multitasking behaviour

The second contribution of the present study is that human-computer-environment fit (H4) was found to significantly enhance the prediction of both self-report and objective behavioural measures of media multitasking. Understanding and exploring models for the interaction between human, computer and environmental factors is critical to HCI research through a temporal lens, apart from studying their roles as separate entities in shaping media multitasking behaviour during an online course (Wiberg & Stolterman, 2021). However, despite the growing recognition of the mutual approach in explaining media multitasking, the interaction mode between different factors remains unclear. By borrowing ideas from the person-environment fit and person-job fit theories (Hecht & Allen, 2005; König & Waller, 2010) about the relationship between an individual's disposition (e.g., preference for multitasking) and their multitasking (Hecht & Allen, 2005; König & Waller, 2010; Madjar, Oldham, Madjar, & Oldham, 2009), our study's findings deepen the HCI field's understanding of how these factors mutually influence each other in shaping media multitasking during an online course. The findings of this study suggest another possible mechanism underpinning media multitasking during an online course, human-computer-environment fit. The core argument of human-computer-environment fit is that congruence between human, computer, and environmental factors improves the prediction of media multitasking on a mobile phone during an online course. This finding not only corroborates the assumption in previous literature that interaction between different factors may be better than single factors in explaining (objective behavioural measures) media multitasking (Magen, 2017; Z. Wang & Tchernev, 2012; Zhang & Zhang, 2012), but it also deepens our understanding of how different factors interplay in forming media multitasking behaviour with the human-computer-environment fit model.

This study's argument about the role of the interplay of different factors in predicting media multitasking is not completely new in the field of human behaviour and human-computer interaction. For instance, although polychronicity is typically considered a stable individual disposition variable describing a person's general dispositional preference for multitasking that barely changes in a situated environment, the function of individual disposition on media behaviour has been suggested to be moderated by the surrounding environment, which is abundant with multiple media streams (Green, 2014; König & Waller, 2010; Magen, 2017; Zhang & Zhang, 2012). In particular, with the prevalence of smart devices (e.g., smartphones) in everyday life, technology has become proactive, alongside human beliefs and behaviours (Rahwan et al., 2019), in shaping users' needs (Sundar & Limperos, 2013). Technology has reshaped the landscape of the environment in which humans live (Ito & Okabe, 2006). It is not surprising that the mutual influence of human factors, computer factors, and environment-related conditions has attracted growing attention in newly emerging theoretical frameworks with respect to human-computer interactions. Theoretical frameworks, such as the techno-social situation (Ito & Okabe, 2006), situated action (Zhang & Zhang, 2012), hybrid human-machine/collective machine behaviour (Rahwan et al., 2019), symbiotic interaction (Gaines, 2019; Jacucci, Spagnolli, Freeman, & Gamberini, 2014), and the Fogg behaviour models (Fogg, 2009), have explicitly argued or implied that humans, technology, and the environment play a co-determined role in shaping human behaviour regarding technology use. It is interesting that even classical UGT has evolved (e.g., context-dependent UGT, dynamic UGT (Green, 2014; Z. Wang & Tchernev, 2012) to accommodate the influence imposed by ED and technology affordance/availability on media multitasking alongside personal preferences and motives. Our study supports such developments in theory.

The significance of the human-computer-environment fit does not mean that a single factor is not significant in shaping the behaviour of social media use. However, the additional prediction provided by human-computer-environment fit suggests that the role of any single factor in shaping the objective behavioural measures of media multitasking during an online course is also dependent on the alignment with other factors. Based on the results of this study, research on time and temporality in HCI should direct some attention away from a single factor-centred approach (e.g., either user-centred or media-centred (Zhang & Zhang, 2012)). Instead, the focus should be towards a mutual approach to discover how the interaction between different factors affects certain behaviours and not others, particularly because the human-computer-environment fit may function in a more complicated way than hitherto expected.

5.4 Methodological implications: How should media multitasking behaviour be approached through a temporal lens

The collection of both self-report and objective behavioural measures of media multitasking behaviour in our study allows us to address different temporal aspects of HCI. Despite the fact that existing literature on media multitasking behaviour in real life is based mainly on evidence from self-report measures, the self-report measures of media multitasking we found to differ from the objective behavioural measures. Additionally, the prediction of media multitasking behaviour by human factors, computer factors, environmental factors and fit of them showed differences between self-report and objective behavioural measures. The results of this present study thus demonstrated it is essential to collect both self-report and objective behavioural measures of media multitasking behaviour and investigate them from different perspectives.

The association of ED with self-report media multitasking during an online course, and its disassociation with the objective behavioural measures, may reflect the association between the perception of multitasking experiences and the multitasking demands. However, the subjective feeling of ED was not powerful enough to result in more frequent media multitasking on a mobile phone or longer time with media unrelated to the course on a mobile phone in real life. Another potential explanation is that the ED in this study was not specifically about demand for media multitasking with a mobile phone.

The failure of predicting the two objective behavioural measures of media multitasking indicates that UGT should probably be constrained to explaining only self-report measures of media multitasking behaviour, on which the existing literature supporting the correlation between MMM and media multitasking behaviour are based (König & Waller, 2010; Kononova & Chiang, 2015; Magen, 2017; Zhang & Zhang, 2012). The differences in association of motives for self-report and objective behavioural measures of media multitasking during an online course indicate that the correlation between self-report measures was possibly due to their interlock at a cognitive and conceptual level. However, this interlock is inadequate to explain gratification or motive as a powerful predictor of media multitasking during an online course at the behavioural level. The discrepancy was potentially caused by the highly fluid and flexible nature of media use on mobile phones due to multi-functionalities and the diverse and dynamic context in which mobile phones are used (Parry & le Roux, 2019; Zhang & Zhang, 2012). The fluid nature of objective behaviour of media use was shown by the weak correlation of FOM between the two weeks. This fluid and flexible nature of objective behavioural measures of media multitasking in everyday life makes it less likely that they are solely determined by personal disposition. The inadequacy of personal motives in predicting objective measures of media multitasking was consistent with the finding of one laboratory study, in which preference for multitasking was measured on a self-report scale (i.e. the Inventory of Polychronic Values) and by objective performance (König et al., 2005). These findings reflected the argument that technology use over time becomes habitual and more ‘absent-minded’ (Ellis et al., 2019), which may disassociate the self-report or estimation of behaviour from objective behaviour. The disassociation of self-report and objective behavioural measures was corroborated by the failure of social motive in predicting FOM and TMM. Although the students reported lower levels of media multitasking during the online course motived by social motive, the logging data showed that 95% of students used WeChat when taking the online course. Another notable finding of the present study is that information motive negatively predicted MMP, which indicates that motive not only acts as a driver of media multitasking during an online course (H1-1), but it may also inhibit media multitasking behaviour (went beyond the prediction of H1-1). A possible explanation for this is that multitasking behaviour was motived by seeking information and may also have created an awareness of restricting the time spent searching for information, thereby maximising the benefits of multitasking and mitigating the downsides.

5.5 Limitations

The findings of this study about objective behavioural measures are based on a sample of 40 mobile phone users, which may limit the generalizability of the findings. Despite the difficulties of collecting and analysing objective behaviour of real-life media multitasking during an online course, future studies should include a greater number of participants to validate the role of self-report and objective behavioural measures of personal, technological, and environmental factors, and their fit in shaping real-life media multitasking behaviour. However, we believe that large-scale studies should only be attempted after a smaller-scale study (i.e., the current study) has been conducted and exploratory studies have reviewed the results of this research, established a conceptual apparatus, and suggested adequate measures for large-scale studies.

The hypothesis of the mutual approach in this study was examined using a human-computer-environment fit, which was inspired by the index of demands-abilities fit and supplies-values fit (Hecht & Allen, 2005; König & Waller, 2010). Although this study corroborated the fit of human factors, computer factors, and environmental factors in enhancing the prediction of media multitasking as expected, it is an open question for future studies whether other aspects of human factors, computer factors, and environmental factors may also explain media multitasking behaviour and whether there are other forms of interplay among them in addition to the FI. In addition, an unclear mechanism underpinning the human-computer-environment fit leaves an avenue for future study. A possible mechanism behind the role of human-computer-environment fit in shaping media multitasking behaviour may be the discomfort caused by cognitive dissonance when an student with a high level of preference for media multitasking studies in an environment with a low level of multitasking demands, is not allowed to multitask, or has no technology that supports media multitasking (König & Waller, 2010).

The self-report reasons for engaging in media multitasking behaviour denotes the significance of interaction within subcategories of WHAT dimension in HCIoT as factors shaping media multitasking behaviour. For instance, students reported that they checked with fellow students in WeChat when the connection was unstable to help make sure whether it was caused by the teacher side or their own side (i.e., interaction within humans). Some students choose to watch the livestream of online course on computer while answer the quiz on mobile phone (i.e., interaction within computers).

6. Conclusion

The results of this study of students' media multitasking in online courses during Covid-19 period support that HCIoT is a promising model for organizing future efforts towards explaining the behaviour of interacting with computers through a temporal lens. The significance of the HCIoT subcategory *over Time*, which addresses the larger temporal environment of HCI such periods, phases, waves of HCI, was evident. In this study the Covid-19 typical *over time* environmental demands' significance for addressing time and temporality of media multitasking in an online course during Covid-19 was exemplified by its significant prediction of self-report measures of media multitasking behaviour, and by its enhanced prediction of both self-report and objective behavioural measures of media multitasking behaviour with the addition of human-computer-environment fit. Thus, compared to the previous richest measure of multitasking (Benbunan-Fich et al., 2011), which takes into account the perspective of user (human), computer, and task simultaneously, the mutual fit index suggested in this paper is a broader measure that can capture the environmental demands typical for a whole period. The use of the HCIoT model subcategories of human, computer, and environment made it possible to account for the environmental stimuli provided by the Covid-19 period way of life (studying online, isolation, disturbance by family members and deliveries, etc.). Furthermore, we found that while the environment subcategory and the human subcategory only predicted the self-report measures, in contrast the computer subcategory predicted both the self-report measures and the objective behavioural measures of media multitasking online course. This variability of the HCIoT subcategories in explaining the media multitasking behaviour denotes a new direction of time and temporality studies in HCI towards investigating the role of the subcategories of the WHAT relative to the HOW dimension's different measurement methods.

6.1 Implications for design for time and temporality

Approaches to time and temporality from a design perspective is a growing field (Odom et al., 2018; Rahm-Skågeby & Rahm, 2021; van Amstel & Gonzatto, 2021; Wiberg & Stolterman, 2021). In our study of students' media multitasking during the Covid-19 period, we found a complexity of personal, human needs and motives, nomophobic mobile phone designs, and Covid-19-typical environmental demands, to predict students' media multitasking in online courses. Furthermore, compared to pre-Covid studies our study indicates less media multitasking by students in online courses, that is, a more serious approach by users to HCI. Therefore, a general design implication of our study is that designers of online course technology should design with the larger temporal context in mind (for a similar argument about changing your tool when the overall paradigm changes, see (Gardien, Djajadiningrat, Hummels, & Brombacher, 2014)). Thus, the Covid-19 period's revelations of a complexity of factors behind media multitasking, and the indication of a decreased media multitasking compared to what was found in pre-Covid HCI studies, call for 'Covid-HCI period' designs.

A design approach that gathers for both the complexity of media multitasking and the seriousness of online courses in the Covid-19 period will allow the students to complete the online course easily on one device without requirement of using any other media than the online course platform. In this design approach, WeChat or other multi-apps that supports easy media multitasking will be the primary way to reduce media multitasking. e-Learning interface systems should support students' easy customization of media multitasking capabilities within a course, see Park and Liu (2012) for a discussion of this. In addition to the customization, our study suggests that the designs should not only allow more multitasking within the online course, but also include support for dealing with the COVID 19 periods typical environmental demands such as delivery boys and family interruptions and more. Such designs offer genuinely improved support for students' main activities during online courses. Furthermore, an additional finding of our study was that media multitasking (MMI) significantly decreased ($\beta = -.17, R^2$=.08, p < .01) when the satisfaction regarding the online course learning increased (M=3.83, SD =0.72). So, any design that increase the students' satisfaction with the online course may help.

The online course platform examined in this study was designed to be used on both computers and mobile phones, and the online course could only be carried out by engaging in multiple media. As reflected in self-report scenarios of using multiple devices when taking an online course, students had to use mobile phones to interact with teachers and classmates and use computers to display the materials of online courses at the same time. In another scenario, scanning the QR code with WeChat account or sending message to mobile phone were required when logging into the online course platform. Thus, a design implication from the Covid-19 period is that the classic HCI design with the aim to reduce media multitasking behaviour may be misguided. Classic nudging interventions directed towards (reducing) the media multitasking itself may solve a problem that became less serious and changed in nature when the Covid-19 period emerged. For example, an 'always on' computer application showing recent time use may successfully reduce students' media multitasking (Whittaker et al., 2016). However, it may work different in a period with less media multitasking and a different combination of HCI factors behind media multitasking. In the online course studied here, all the materials were moved to online from off-line course in short period of time after the outbreak of COVID-19, and still the students showed less media multitasking. Furthermore, as demonstrated by the various motives for media multitasking behaviour, future designs for online courses should support experiences that go beyond efficiency and include moments of mental rest, social connection, meaning-making, slowness, etc. (Fawns, Aitken, & Jones, 2019), some of which is best achieved with media multitasking.

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