Vision: The intensity of childhood screen exposure is increasing year-on-year. In 2022, UK children watched on average 9.6 hours of broadcast TV or on-demand video per week (~15.5% of their waking life), with 81% of toddlers using touchscreens daily[1]. Content is increasingly streamed online, with only 33% of children watching whole TV shows or movies compared to 65% watching short online videos via apps such as Youtube and TikTok[1]. The sensory-cognitive stimulation provided by screens far exceeds that of reality, potentially shaping cognitive development during the first few years of peak neural plasticity. Concerned parents, policymakers, and scientists have long questioned the potential impact of screen time on young children's cognitive development, with some authorities recommending a ban on screen time before 18 months-of-age (American Academy of Pediatrics[2]) or extreme caution on the duration and type of content shown to children (UK Chief Medical Officers[3]). But such recommendations often fail to appreciate the potential educational benefits of age-appropriate content designed with child development in mind[4]. For example, the design of children's animation is informed by decades of inherited craft knowledge and creative intuition about how to fit the demands of the audio-visual stimuli to the constraints of the developing mind[5]. We have shown that these insights result in stimuli that simplify the processing demands on viewers compared to adult-directed media and allow young children to attend in an adult-like way[6]. The success of shows that use these techniques, such as Numberblocks (Blue Zoo/BBC) are appreciated by early-years educators who commonly integrate them in the classroom, even without a scientific understanding of how and if they work. The craft insights of animators and children's TV producers exceeds the scientific understanding of how children cognitively process such complex stimuli[6]. As the UK children's media industry now faces the legal threat of not-complying with the Age Appropriate Design Code (i.e. the Children's Code[7]; part of UK GDPR law; rooted in the United Nations Convention on the Rights of the Child), combining the craft knowledge of children's TV producers with the insights of developmental scientists to characterise the age appropriateness of digital content **is timely and of pressing societal importance**. But gaining such theoretical and scientific insights would only go part of the way to providing a solution for the UK creative industries who need tools to guide their creative process and indicate if their content is appropriate for particular viewers. With the recent advances in artificial intelligence (AI) and deep learning classifiers of video content[8], building age-appropriate classifiers for video clips trained on neurocognitive markers is possible. The **vision** of the *Animating Minds* project is to ***triangulate*** **the cognitive impact of media at different developmental stages** by examining the question from the perspectives of practice, theory, psychology and computation. By establishing **a transdisciplinary dialogue**, this project will blur discipline boundaries and **establish a world-leading UK-wide network in applied neurocognitive development** that can directly benefit the creative industries.

Fundamental to the whole concept of 'age-appropriate design' is designing media content and services that are tailored to the needs of children at different stages of development[9]. Age guidance for certain aspects of media design, e.g. sexual or violent imagery, adult themes, is well established in the UK (enforced by the British Board of Film Classification). However, less is known about the demands that media experiences place on cognition: is information presented in a way that aids understanding, or does it overwhelm the limited cognitive capacity of young children? Developmental science has shown that immediately after viewing fast-paced fantastical cartoons, young children exhibit lower ability to focus attention, learn, retain information and follow rules (a suite of cognitive skills known as executive functions, EF)[10]. Our group has demonstrated associations between increased screen time during early childhood and an inability to inhibit distractors[11] together with poorer EF[12]. But not all media experiences are the same: exposure to educational TV rather than adult-directed TV can ameliorate negative EF effects[4]. The *Animating Minds* project will focus on children's EF measured via novel child-friendly behavioural tasks developed by our team[12] which enable detailed EF measures to be collected at scale, together with in-lab naturalistic eye-tracking and functional Near-Infrared Spectroscopy (fNIRS), neurocognitive methods specifically suitable for children. These markers will be used to validate creatives' intuitions about how features of media design may overwhelm or facilitate children's cognition as well as to train machine learning classifiers which can predict how new animated content will impact children's EF at different ages. The resulting transdisciplinary knowledge and methods will radically expand our psychological, practical, computational and theoretical understanding of children's media.

Approach: The interdisciplinary goal of the *Animating Minds* project is to triangulate the impact of animation on children's neurocognition and concretise this insight as an AI tool. Specifically, we focus on children's executive functions (EF) across key developmental stages (3-6 years; a period of EF maturation, neurocognitive development and a transitional age in terms of TV programming, e.g. CBeebies to CBBC). To achieve our ambitious goal, we will elicit and formalise expert insight (O1), train a machine learning (ML) classifier on expert (O2) and empirical data (O3) and validate the insights and classifier with neurocognitive data (O4). Alongside the collective goal, achieving the objectives also represents significant innovation within each discipline and requires cross-discipline input across constituent work package activities: Practice, Theory, Psychology and Computation.

Objective 1: Reflecting on creative practice. The humanities approach to animation studies often focuses on theoretical or sociocultural aspects[13], rather than the process by which animators tailor content for specific audiences. Psychological approaches to testing animation effects (e.g. the effect of fantastical content on child cognition[10]) often conflate the formal aspects of animation (e.g. pacing, intensity) with the content[14]. In O1, we address the impact of animation by taking a mixed methodology approach across a series of industry workshops (Work package 1, WP1; see Gantt chart). The project benefits from an unprecedented level of commitment from the UK animation industry (see Letters of Support). Our Advisory Board (AB) will include key representatives of the UK animation industry, media foundations and early-years educators (see Project Partners). The AB will guide the overall project and facilitate contact to a network of animators and producers (our Creator Panel; CP) who will participate in a series of knowledge exchange (KE) workshops. The workshops will be run by PT and MG, who have expertise using mixed-methods approaches to understand creative practice[15,16]. Workshops will be facilitated by Flow Associates, experts in qualitative investigations of arts practice who will use a range of methods to encourage animators to reflect on the explicit and implicit ways in which they tailor content for specific age viewers. Qualitative and quantitative data will be gathered through questionnaires, focus group exercises, clip analyses and one-on-one semi-structured interviews. Common approaches, considerations and heuristics will be identified via thematic analysis. These creative insights will be utilised in subsequent workshops to aid reflection and encourage further insights which incorporate the project's scientific and computational outputs (WP2-4). Utilising Flow's Threshold Model of engagement we will track how our industry partners progress from being informed through to being empowered to change their practice based on the project's outcomes[17]. The KE workshops will be timed to precede and feed into critical decision points (see Gantt Chart) to ensure our workplan is co-created with industry. For example, the insights emerging from workshops 1 and 2 will inform the criteria we look for in the pre-trained backbone to our ML models (WP2) and help rank cinematic features in terms of their hypothesised importance in predicting EF impact (WP3). The AB/CP will also advise and facilitate the creation of our unique children's animation corpus (~1500 episodes, across ~300 series; WP1), large enough to facilitate ML (WPs 2, 3, & 4) and regression analysis (WP3). Existing video corpora are lacking in children's content[18], too small[14] or too varied in their content type[19]. Our AB/CP members have already committed access to 296 episodes for which they own copyright and will facilitate further access through their industry networks.

Objective 2: Machine learning of children's animation age ratings. A key step towards training a ML classifier is data annotation for each exemplar. In our case, the ground truth annotations required are the impact each video clip has on the EF of 3- to 6-year-old children. Such empirical annotations are considerably more complex, costly and time consuming to acquire than a simple categorisation task (e.g. whether an image is a "cat" or "dog"), requiring a sample of participants to derive an average response to each clip. The common rule-of-thumb for the minimal training dataset size for supervised learning is at least 1000 exemplars per class[20] (and several orders more if training a deep learning classifier from scratch[21]). As annotating 2000 videos (1000*2 for EF depleting vs not) is unfeasible given the number of child viewers required, we will instead leverage a common ML technique to decrease the required corpus size: *transfer learning[20]. Transfer learning* will be used to retrain existing ML models proven to work with related content and classification tasks. We will start by retraining existing video classification models (AnimeCNN[22] and ACLNet[23], see descriptions below) on a proximal classification: *age ratings*. This is an important first step, because a video clip's EF depleting effect is related to target age appropriateness[14] (e.g. *SpongeBob Squarepants*, which is recommended for 6+, reduced EF in 4-year-olds, while Cailou, target age 3+, did not[10]). We will capitalise on this age-effect, building a model over three stages transferring model learning from numerous but coarse annotations (expert-assessed age ratings, WP2), to fewer but more precise annotations of behavioural (WP3) and neurocognitively validating its predictions (WP4).

Model 1 will be trained to predict the CommonSense media age-appropriateness rating for each video clip[24]. These ratings are produced by child development experts (e.g. 2+, 3+, 4+, 5+, 6+ years) and will be checked by our industry experts (WP2). These age ratings conflate various aspects of the content appropriateness including language, violence, sexual imagery etc., but also the cognitive demands that each show places on the viewer (Note: our corpus will only contain BBFC U/Universal certified content). Our choice of existing ML models to combine and predict these age ratings will be inspired by psychological research showing that EF depleting animations contain denser cinematic features and are more visually salient (i.e. attract more attention[14,6]). Two existing convolutional neural network (CNN) models that predict cinematic features in animations and visual saliency will be used. AnimeCNN, developed by our visiting researcher, Sergio Benini (SB) is trained to classify cinematic features (camera level, camera angle, and shot scale) on animated content[22]. This model will be combined with ACLNet, an Attentive Convolutional Neural Network with Long Short-Term Memory trained to predict visual saliency and corresponding human overt attention patterns in videos[23]. To combine these models, we will use *hybrid* multiple model learning. This is similar to ensemble learning, where a range of models are used to predict an outcome. However, rather than using an additional model to increase the performance of the first, predictions from two or more models will be combined using weighted voting. This combined model should be able to identify features implicit in the existing models including the spatiotemporal patterns of cinematic features, rudimentary scene semantics (e.g. object and face locations, depth, scene structure, etc), visual saliency, and the dynamics of human attention over our animation videos. To train the combined model on the age ratings we will add a new classification layer which takes input from the classification levels of the component models (Anime CNN and ACLNet) and iterates through a rapid-cycle of training (900 age-rated videos), validation (150 videos) and test (450 videos). Specific instances of model failures will be fed back to our CP experts (WP1) to gain insights into which features may be being missed by the model and test whether new feature detectors can be engineered into the model to improve performance.

Objective 3: Predicting behavioural EF associations across videos. To move from the practical insights emerging from WP1 regarding factors impacting children's EF and the proximal model predictions of age ratings (WP2) to *a model that can directly predict EF impact* we need to annotate our video corpus with EF data. Prior work testing which features of a video are associated with EF depletion only use a limited number of clips[25]. In such a small between-video design, the contributions of specific features (e.g. character or event changes, the frequency of cinematic features) cannot be isolated from other confounding differences between videos. Regression analysis of associations between feature-dimensions and EF demands could begin to provide such insights, but a large number of clips are required, which is unfeasible using traditional developmental lab studies. In the *Animating Minds* project, we propose to overcome this problem by employing a novel online, caregiver-assisted behavioural EF test to a large subset of our animation corpus. We will use an online adaptation of the classic Delayed Alternation (DA) task[26], which measures a child's ability to alternate between screen locations to find a rewarding video, using executive control to inhibit the prepotent response to repeatedly select the same location[27]. The DA task will be performed before (baseline) and immediately after watching a video from our animation corpus. As the EF demands of each video will vary across individuals, even within the same age group, multiple viewers are required for an average EF response per video. Based on pilot analysis of the online DA test administered across a similar age range[27], 8 participants will be sufficient to capture the large age effect on proportion correct (Cohen's f=0.639, alpha= .05; power=.80). We will oversample

(N=16) for each video, to account for online data loss and participant drop-out. Similar sample sizes (~16) are common in studies gathering neurocognitive annotations for training ML classifiers[28,29].

In WP3, we propose to gather online EF data for a subset of videos selected from our corpus, that represent full coverage of the existing age ratings and variation in clip properties. Cinematic features (e.g. cut rate, motion, image clutter, average shot scale, num. characters per shot) will be automatically quantified for all clips using existing computational tools[8,19,31] and candidate clips that cover the full range of these metrics will be selected with guidance from our CP (WP1). This online study will occur in parallel with ML of the age ratings (WP2) so that the results (i.e. average EF rating for each video at each age) will be available in time for integration into the model and retraining (Model 2). The stimulus set size chosen - 161 videos - is powered from a small prior analysis of features predicting EF depletion[14]: based on an odds ratio of 0.41 for the 'discontinuous edits' feature, Pr(Y=1|X=1)=0.5, R^2=0.65, alpha=.05, power=.80, assuming a normal distribution for discontinuous edits, 158 clips are required. The set of 161 videos will be divided into 10 video sets (17 total clips/participant - 16 + 1 cross-validation video). Each video set will be viewed by 16 participants in each of two age groups (3 & 6 years; total participants N=320). To limit any spill-over effects of a given video clip, families will be sent a link to participate in maximum of one experimental trial per day (i.e. DA baseline task, video clip and DA post-viewing task; ~15 mins duration). Previous developmental studies conducted by TS and RB have demonstrated that recruiting large samples of families online is feasible (e.g. ~1100 families for an extensive questionnaire study[30]; and 117 for the pilot online DA task[27]) and such online behavioural developmental studies are becoming common[32]. Participant families will be recruited from the QMUL Babylab database (RB), affiliate Babylab databases (Birkbeck; Bath; Goldsmiths; Essex; Bristol; UEA) and advertised by our AB's extensive social media and membership networks. We will target broad socioeconomic (based on index of multiple deprivations; IMD) and ethnic diversity by utilising our previously successful approaches including advertising via children's centres facilitated by the EYA e.g. in our Parent-Administered Screen Time Intervention (PASTI) study[33]. The empirical output of WP3 will be a highly unique, large-scale investigation of behavioural EF across a varied video stimulus set that will **advance multiple fields** including animation theory and developmental science through its findings and open data.

Objective 4: Neurocognitive validation. The WP3 results can elucidate the association between video features and EF demands at different ages, but this approach cannot rule out the effects of confounding factors. In other words, it is not possible to determine whether particular features are *causing* EF depletion. Animators often use redundancy to ensure that all aspects of a video contribute to a consistent style and match the content and intended impact of a video[34]. Here, to directly test the intuitions of animators (WP1), and the predictions of our ML model (WP2&3), we will experimentally compare the impact of *manipulated versions of the same videos*. Our creator panel will advise on modification of two existing video clips (one targeted at 3-year-olds, one at 6-year-olds), to adapt the animation to be more appropriate for the EF capacity of the opposite age group. Candidate features for manipulation will be suggested by our CP (WP1), developmental experts (RB, PP & TS) and analysis of extracted video features in our age-rated corpus (WP3). Children (aged 3 and 6 years) will be shown both video clips (age-matched vs. not age-matched) in a within-subjects design. To allow calibration between the online and lab study, the same DA task will be administered pre- and post-video. To move beyond a static snapshot of the consequence of a video on EF and begin elaborating how EF is challenged by the audio-visual content during viewing, we will employ real-time neurocognitive measures. High-speed eye-tracking will be used to record executive attention and information processing patterns during the clip (e.g. fixation durations, scan paths, gaze dispersal[35]) and immediately afterwards via a saccade contingent executive attention task (anti-saccade task[11]). A real-time measure of neural activation associated with EF activity will be provided by wearable functional Near-Infrared Spectroscopy (fNIRS). Neural activation is associated with an increase in oxygenated haemoglobin (HbO_2) and a decrease in deoxyhaemoglobin (HbR). Functional NIRS can noninvasively measure HbO_2/HbR changes in brain areas associated with EF activity in children during naturalistic tasks without contamination of motor artefacts (being based on light rather than electrical signals like EEG[36]). EF is known to be associated with prefrontal cortex

(PFC[37]) activation. We have demonstrated PFC activation differences during tasks differing in EF demands in 3- and 6-year-old children[38]. In WP4, by using fNIRS to record continuous PFC activation during viewing of our manipulated videos we will be able to quantify the real-time EF demand of each video, providing a direct test of our experts' creative intuitions about how to design the content to be more-or-less demanding. The sample size calculation is based on our previous work testing how matched animations (Looney Toon cartoons[39]) with and without fantastical events, impact toddlers' ability to inhibit saccades to a distractor in the antisaccade task: Cohen's d=0.386, alpha=.05, power=.80, indicates a sample of 60 (N=55 + 10% accommodating data loss) is required to replicate this effect in each age group (N=120 total). Data will be analysed using generalised estimating equations, with robust standard errors and an unstructured correlation matrix, to account for the repeated measures design and enable inclusion of participants with partially missing data (i.e. in one video clip condition).

The multimodal behavioural, eye movement and brain activity markers of EF demand during the two versions of the video clip will be combined into a composite EF-impact score and compared to the predictions of the EF model for these videos. Any discrepancy between the ML model predictions and the empirical results will be used to inform further model refinement and feature engineering by adding specific feature detectors identified by the experts as being critical to the difference between clips. The rich neurocognitive EF markers will allow us to not only identify when a clip results in "too much" or "too little" EF demand for a particular age group, but also when it provides the optimum level of challenge for their developing cognitive capacities. This "Goldilocks" zone is known to be important for helping a child acquire new knowledge and skills, typically considered in terms of the sensitive support of a caregiver or more knowledgeable peer who can scaffold their learning[40]. Children's animation, designed in the right way to ensure a child's EF is not overwhelmed, may function in the same way as a sensitive teacher and place the child in a receptive cognitive state to learn. The methods and computational tools created during this project have the potential to help future creators design their content to maximally benefit child learning.

Workpackage		Activity	M1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
WP0 (Lead: TS)	0a	Monthly online team progress meetings		x	x		x	x		x	x		x	x		x	x		x	x		x	x		x	
Management	0b	Quarterly in-person team meetings + End of Project	x			x			x			x			x			x			x			x		x
WP1 (Co-Leads: PT+MG)	1a	Advisory group meetings	x									x														
Reflecting on Creative Practice	1b	Creator Panel co-creation and KE workshops	x			x						x									x					
	1c	Collect videos (1500 episodes, across 300 series)	x	x																						
	1d	Implications for creative practice ('Futures') workshop																								x
WP2 (Co-Leads: MG+TS)	2a	Extraction of commonsense media age classifications	x	x																						
Machine Learning of Age Ratings	2b	Expert validation of age classes - Online Survey		x	x																					
	2c	Mod-1: Build ML framework (source and adapt existing models)	x	x	x	x																				
	2d	Mod-1: Train, test, tune classifier on Age Class data (1500 exemplars)				x	x	x	x	x	x	x														
WP3 (Co-Leads: TS+RB)	3a	Identifying AV features to capture	x																							
Predicting Behavioural EF	3b	Adapt existing computational tools		x	x	x	x																			
	3c	Applying tools to video corpus				x	x																			
	3d	Expert-guided regression analysis of features for varied clip selection					x	x																		
	3e	Design & build online experiment (161 clips across 5 video sets)					x	x	x																	
	3f	Recruit participants (N=320, 160 per age: 3 & 6 yrs)							x	x	x	x														
	3g	Run experiment online								x	x	x	x													
	3h	Analysis, Data Archiving & Reporting											x	x	x	x	x									
	3i	Mod-2: Adapt framework for Online EF data										x	x	x												
	3j	Mod-2: Train, test, tune classifier on online EF data												x	x	x	x	x	x							
	3k	Mod-2: Network bending to optimise feature preferences																	x	x						
WP4 (Co-Leads: RB+PP)	4a	Design age-based diffs. informed by expert insight and regression analysis					x	x																		
Neurocognitive validation	4b	Video creation						x	x	x																
	4c	Design, build and pilot neurocog experiments							x	x	x															
	4d	Recruit participants (N=120 participants, 60 per age: 3 & 6 yrs)								x	x	x	x	x	x	x	x	x	x							
	4e	Run experiment in lab (testing rate = 3 per week/12 per month)									x	x	x	x	x	x	x	x	x	x						
	4f	Analysis, Data Archiving & Reporting																		x	x	x	x	x		
	4g	Mod-3: Test classifier on Lab EF data																				x	x			
	4h	Mod-3: Expert-led Feature Engineering to optimise model																					x	x	x	x
	4i	Mod-3: Model Reporting & dissemination																							x	x

Discipline:
Practice
Theory
Psychology
Computation
All

Gantt chart: Timing of work package (WP) activities over the 24-month project (M1-24).

Risks & Mitigation: A bold interdisciplinary project like this always comes with risks. Our teams' collective interdisciplinary expertise, and the skills developed through running previous large-scale, multi-site and interdisciplinary projects will help mitigate against many of the most common risks. Key risks and mitigations: 1) lack of content provision by industry partners or issues with copyright: likelihood=low, mitigation - content will be sourced from publicly available websites (e.g. Youtube) or DVDs; 2) unavailability of ML models pretrained on similar tasks, likelihood=low, mitigation – models trained on less related image classification tasks will be used; 3) Failure to recruit sufficient families online, likelihood=medium, mitigation - extend our advertisements to international English-speaking partner developmental labs, e.g. Boston, UPenn, McGill, 4) Delays in manipulated content creation: likelihood=medium, mitigation - post-production digital manipulation of existing content is an alternate method to alter features that does not require new animation to be created; 5) Ethical concerns about the use of AI may be voiced by our industry partners; likelihood=medium, mitigation - actively engage with this discussion to ensure our tool is designed with their concerns in mind, including with the guidance of our AB ethics expert.

Environment: The *Animating Minds* project is made possible by the unique interdisciplinary research environments provided by our team. UAL is 2nd in the QS World University ranking in art & design and the UAL Creative Computing Institute (CCI) is a world-leading centre in developing computational approaches to understanding and enabling creativity. Leading on the computational and online experimental studies (WPs 2 & 3), CCI's research infrastructure will be invaluable to the project's success including dedicated high-performance GPU computing clusters for ML, in-person and online research facilities including online experimental tools, participant databases and dedicated research and technical staff with experience spanning the experimental methods required for this project, including eye-tracking and fNIRS (to support WP4). This project will also benefit from CCI's extensive experience in KE and industry collaboration via dedicated KE staff, a business incubator and links to national and international arts and technology festivals. The KE and animation industry connections (WP1) will be made possible by the Arts University Bournemouth's track record in training world-leading animators and linking its teaching and research practice directly with industry. QMUL's School of Biological and Behavioural Sciences is a diverse, cutting-edge scientific environment, which will lead on the developmental science component of the project (WP4 and supporting WP3) via the QMUL Babylab, directed by RB. The QMUL Babylab houses a dedicated child-friendly, testing suite including the state-of-the art experimental equipment required by the project and extensive expertise in utilising the intended paradigms across our target age range. The analytic advances necessary to interpret the real-time EF demand of videos via fNIRS (WP4) will be made possible by the world-leading neurodevelopmental methods within the Birkbeck Centre for Brain and Cognitive Development (CBCD) ToddlerLab, coordinated by PP.

Outcomes and Impacts: The aims and objectives of the *Animating Minds* project are only made possible by breaking down disciplinary boundaries and synthesising across theories, methods and research cultures from traditionally separate disciplines. By synthesising across multiple perspectives and working closely with key industry voices we aim to provide the foundation *for translating our project outcomes into impacts*. While the project aim is to triangulate the impact of animation on children's neurocognition and manifest this insight as an AI tool (output: open access publication in an IEEE journal and public GitHub model code release), each work package will also make significant contributions to their respective disciplines and demonstrate new modes of interdisciplinary collaboration. Animation studies will gain detailed practical insights into how animators design content for specific ages and computational tools which can facilitate testing of future animation theories (outputs: a monograph by PT and GitHub release of code). The empirical lab-data will significantly advance the developmental science field in terms of understanding how screen media *directly impacts EF in real-time* using co-registered naturalistic fNIRS and gaze behaviour (outputs: top tier Q1 journal publications and international conference presentations). Animators will benefit from the insights that developmental and computer science can provide to their creative practice (outputs: short accessible videos, blog posts and industry conference presentations co-produced with AnimationUK, CMF & EYA). Potential future impacts: 1) Extensions of the ML classifier to the EF demands of other visual contexts e.g. videogames, apps or a child's real-world environment recorded via head-cam footage; 2) Creative AI may use the neurocognitively-informed model of dynamic scene processing to form the foundation of generative AI systems capable of creating new video footage to fit specific EF profiles. The societal impact of this project and those that build on its approach cannot be underestimated. At a time of rapid proliferation of media technologies and increasing penetration into all aspects of a child's environment (as legally acknowledged by the ICO Children's Code[7]), tools and insights like those produced by the *Animating Minds* project will be essential for parents, policy makers and the media industry to better understand the role screen media plays in child development and how to nurture the best outcomes.

Strategy to co-deliver the research.

The *Animating Minds* project **aligns clearly with the scheme objectives:** it was conceived of and co-designed by an interdisciplinary research team and the project aims and objectives are only achievable by combining approaches, methods and research cultures across multiple disciplines with the creative insights of industry. Our work will be guided by our Advisory Board made up of key figures in the UK children's media, animation and early-years education sectors (Kate O'Connor, Chair, Animation UK; Greg Childs OBE, Director, Children's Media Foundation; Neil Leitch, education expert, Early-Years Alliance; Oli Hyatt MBE, animator/founder, Blue Zoo; Miki Chojnacka, CEO, Sandbox Kids; Prof. Kaska Porayska-Pomsta, expert in AI, education and ethics, UCL-Institute of Education), and Creator Panel of animators and directors who will participate in KE workshops (e.g. Steve Smith, Beakus; Duncan Raitt, Plastic Milk). The interdisciplinary, co-led project combines perspectives from animation theory (Dr. Paul Taberham, PT, Arts University Bournemouth), media AI (Prof. Mick Grierson, MG, Creative Computing Institute, UAL), developmental psychology (Prof. Rachael Bedford, RB, Queen Mary University of London), developmental neuroimaging (Dr. Paola Pinti, PP, CBCD), led by cognitive film theorist, Prof. Tim Smith (TS, Creative Computing Institute, UAL). The scope of the project and the **team's experience cover a range of UKRI councils** including AHRC (PT, MG, TS), ESRC (RB, TS), EPSRC (MG, PP, TS), BBSRC (PP, TS), and MRC (PP, RB, TS). Disciplinary differences in modes of enquiry, language and expectations can sometimes derail such projects. We aim to mitigate against this via established partnerships within the research team and the cross-disciplinary experience of the project PI (TS).

To maintain interdisciplinarity at the core of all project activities, each work package will be led by two or more senior academics from different disciplines and involve sub-activities drawing from all of the constituent disciplines: Animation Practice, Humanities, Developmental Science, Neuroscience and Computation (see Gantt Chart, Figure 1). Monthly online research team project meetings will provide an opportunity to track progress, identify developing problems and dynamically adapt the research plan as a collective. A shared digital workspace (Slack) and regular virtual meetings across sites will help offset the issues of collaborating remotely. Quarterly in-person team meetings will help foster a positive and conducive research environment and work against the tendency for the disciplinary sub-groups to retreat to their respective siloed ways of working. These in-person meetings are scheduled to coincide with the AB meetings and CP KE workshops. Through participation and contribution to the KE workshops, we hope to empower all members of the team to think deeply about the practical implications of their work and learn from the creative practitioners.

The PDRFs will work collaboratively across their tasks, combining approaches from their respective source disciplines and broadening their skills so that by the end of the project their skillsets will be truly interdisciplinary. This will be facilitated by CCI providing free access to all of the course material, videos and software associated with their BSc and MScs in Creative Computing, and Data Science and AI for the Creative Industries degrees. The outputs of this project will stand as a demonstration of the potential for applying new methods across disciplines and as calling cards for the early career researchers. For example, the computational feature analysis toolkit developed in WP3 will accelerate the pace and depth at which arts and humanities researchers can study animated content. Existing studies of EF depletion in children are limited by their ability to only test the impact of a small number of videos[10] whilst animators can infinitely experiment with the form of their content but traditionally have no way to confirm their intuitions[13]. The video corpus and manipulated content (produced in WP4) will be invaluable for future empirical investigations.

By **co-designing our research plan** and working **collaboratively across disciplines** towards a single aim **the potential reciprocal benefit to each discipline is great**. This project will establish working procedures, theoretical frameworks, experimental and computational methods for studying the end-to-end impact of children's media that will benefit the traditionally siloed disciplines and provide a framework for future studies.