

Supporting meaningful and adapted experience to foster motivation and sustained engagement

Audrey Serna

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Supporting meaningful and adapted experience to foster motivation and sustained engagement.

SPECIALITE :
Informatique

par
SERNA, Audrey

Soutenue le 11/12/2024 devant la Commission d'examen

(par ordre alphabétique)

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Abstract

I am interested in understanding more thoroughly how users can be supported when interacting with multi-surface, immersive, and gamified environments, managing complexity, and addressing non-instrumental needs. Beyond the instrumental aspects, shaping positive and flourishing user experiences, supporting well-being, and designing meaningful and engaging situations have attracted increasing interest. In this context, my research has focused on investigating how interactive systems should be designed to provide properties, functionalities, and affordances grounded in psychological theories that support users in their activities, create meaningful and adapted experiences, and foster motivation and sustained engagement.

My work is structured around three strongly interrelated research axes, each raising several challenges that I have addressed in the various studies I have conducted. *Research Axis (1)*: Observing and understanding users' activities and experiences with technology to inform the design. This involves conducting ecological and laboratory studies that primarily yield empirical contributions and design recommendations, and defining behavioral analysis methods that lead to methodological contributions. I am particularly interested in investigating several aspects of user experience and behaviors, including motivation, engagement, immersion, social interactions and collaboration. *Research Axis (2)*: Modeling users' characteristics, activities, and experiences, grounded in theories and relying on empirical findings, leading to methodological contributions. This is achieved through the use of statistical approaches to model the influences of users' characteristics on user experience. *Research Axis (3)*: Designing tailored or adaptive interactive systems, leading to technical and design contributions. This is achieved through the development of prototypes that provide specific affordances, tailoring and dynamic adaptation algorithms, and tools to support design choices.

Regarding my research project, I have begun to explore hybrid environments that combine digital and physical settings with heterogeneous devices. These environments create opportunities for the completion of complex tasks and fostering social interactions, but also raise several challenges related to discontinuities in interaction, motivation, communication, and, more broadly, collaboration. I thus outline my research perspectives in response to these challenges by proposing research avenues for 1) supporting meaningful experiences and 2) supporting sustained engagement through adapted experiences.

Acknowledgements

First, I would like to express my gratitude to Wendy Mackay, Jean-Claude Martin and Vero Vanden Abeele for accepting reviewing my work. I am grateful for their time and valuable insights. I also want to thank Sophie Dupuy Chessa, Christophe Garcia and Mohand-Saïd Hacid for participating to my jury.

I am deeply grateful to Elise Lavoué whose support and encouragement have been invaluable throughout this journey. Our first collaboration started when she involved me in Ludimoodle project with the supervision of Stuart Hallifax's PhD. It has been a highly fruitful and inspiring collaboration that continues through numerous projects, and that will last, I hope, for a long time to come.

My gratitude also goes to the PhD students, postdoc and M2 interns that I co-supervised, as many of the contributions presented in this manuscript are the result of our collaborative efforts: Tung Nam Ly, Lili Tong, Guillaume Loup, Stuart Hallifax, Anthony Basille, Qinjie Ju, Nihal Ouherrou, Anne-Laure Guinet, Valentin Lachand Pascal, Sophie Villenave, Anagael Pereira, Marceau Nahon. I really enjoy working with each of them and I am happy that they have already embarked on a successful career. I am also excited to be starting new research with the co-supervision of Niels André and Valentin Midez.

I would of course like to thank my co-authors and the colleagues with whom I co-supervised these students: Samir Aknin, Jörn Hurtienne, Sébastien George, Aurélien Tabard, Jean-Charles Marty, Benoît Encelle, Mathieu Loiseau, Guillaume Lavoué, Diana Nurbakova and Elise Lavoué.

More generally, I would like to thank all the colleagues with whom I worked on my various research projects. I also extend my thanks to all the members of SICAL. We are lucky to have a research team in which we can have pleasant and stimulating discussions.

Lastly, I wish to express my sincere gratitude to my family and friends for their support, encouragement and belief in me.

Thank you all for being an integral part of this achievement.

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Acronyms

AI Artificial Intelligence . . . 141
AMS Academic Motivation Scale . . . 31
AR Augmented Reality . . . 16
DSAA Dimplôme Supérieur d'Arts Appliqués . . . 136
BPNT Basic psychological needs theory . . . 27
BPNSS Basic Psychological Need Satisfaction Scale . . . 31
CET Cognitive Evaluation Theory . . . 26
CSCL Computer Supported Collaborative Learning . . . 16
CSCW Computer Supported Collaborative Work . . . 46
DEG Digital Epistemic Games . . . 74
DMC Dynamics, Mechanics and Components . . . 91
HCI Human Computer Interaction . . . 13
IPP Immersion, Presence, Performance . . . 44
IPQ Igroup Presence Questionnaire (IPQ) . . . 45
LA Learning Analytics . . . 141
METUX Motivation, Engagement, and Thriving in User Experience . . . 36
MR Mixed Reality . . . 16
MSE Multi Surface Environment . . . 16
OIT Organismic integration theory . . . 27
PDEG Pervasive Digital Epistemic Games . . . 75
PENS Player Experience of Need Satisfaction . . . 17
PXI Player eXperience Inventory . . . 17
PQ Presence Questionnaire . . . 45
PLS-PM Partial Least Squares Path Modeling . . . 103
SDT Self-Determination Theory . . . iv
SICAL Situated Interaction, Collaboration, Adaptation, Learning . . . 13
SIMS Situational Motivation Scale . . . 76
SUS Slater Usoh Steed Presence Questionnaire . . . 45
SPI Social Presence Inventory . . . 45
TPE Therapeutic Patient Education . . . 136
TPI Temple Presence Inventory . . . 45
UES User Engagement Scale . . . 37
UI User Interfaces . . . 13
UX User eXperience . . . 13
VR Virtual Reality . . . 16
VE Virtual Environment . . . 79

Part I.

CV and Activity Report



AUDREY SERNA

22/12/1979
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INSA de Lyon, Laboratoire LIRIS, UMR 5205 CNRS
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Parcours professionnel et académique

2022-2023 : **CRCT** de 6 mois accordé par le CNU section 27
Depuis sept. 2010 : **Maître de conférences** en informatique. INSA de Lyon, département Génie Industriel, laboratoire LIRIS
2008-2010 : **Post-doctorat** en Interaction Homme-Machine et Ergonomie. Université Joseph Fourier, Grenoble. Laboratoire LIG, Équipe IIHM.
2005-2008 : **Doctorat** en Informatique et en Sciences Cognitives. Thèse en cotutelle internationale : Université de Sherbrooke, Laboratoire DOMUS (Québec, Canada) et Institut National Polytechnique de Grenoble, Laboratoire TIMC-IMAG (France). « Observation et modélisation des processus exécutifs et de leur dégradation lors du vieillissement cognitif dans la réalisation des activités de la vie quotidienne. Étude pour la conception d'un système d'assistance. ». Allocation doctorale de région Rhône-Alpes.
2005-2008 : **Monitrice** en informatique. Centre d'Initiation à l'Enseignement Supérieur de Grenoble. Université Joseph Fourier, Polytech'Grenoble
2003-2004 : **Master** en sciences cognitives. Institut National Polytechnique de Grenoble. Laboratoires DOMUS de Sherbrooke (Canada) et TIMC-IMAG de Grenoble (France).
Fév. 2003 - Juil. 2003 : **Ingénieur** Informatique. Mabyc SA, Barcelone (Espagne), Recherche et Développement, Département Logiciel.
2001-2002 : **DESS** Génie Informatique, option Ingénierie du logiciel - Mention Bien. Université Joseph Fourier, Grenoble.

Principales responsabilités institutionnelles

2020-2023 : Comité d'évaluation ANR CE33 « interaction, robotique », présidence pour l'AAPG 2022 et AAPG 2023, vice-présidence pour l'AAPG 2021, membre du comité pour l'AAPG 2020
2021 : Membre de l'équipe Mobilité Internationale au département Génie Industriel de l'INSA
2020-2024 : Membre du comité de pilotage du Labex ASLAN de l'Université de Lyon
Depuis sept. 2019 : Responsable d'équipe adjointe de l'équipe SICAL – LIRIS
2013-2015 : Trésorière de l'AFIHM (Association Francophone d'Interaction Homme-Machine)

Principales responsabilités scientifiques

2023-2024 : Co-responsable du groupe de travail EduIHM (IHM pour l'Éducation) affilié à l'AFIHM et l'ATIEF
2020-2022 : Co-porteuse du groupe de travail #GTNUM#interactionhybridation financé par la Direction du numérique pour l'Éducation (DNE).
Depuis 2020 : Membre du comité de suivi des doctorants du LIRIS, école doctorale InfoMaths 512
2019-2022 : Membre de la cellule médiation du LIRIS, responsable médiation de l'équipe SICAL
2011-2015 : Membre du conseil d'administration de l'AFHIM (Trésorière

Prix et distinctions

2019 : Prix mention honorable pour un article présenté à la conférence ACM CHI PLAY 2019 (top 13%)
2017 : Prix du meilleur article étudiant présenté à la conférence internationale CSEDU 2017
2015 : Prime d'Encadrement Doctoral et de Recherche (PEDR), renouvelée en 2019
2006 : Prix du meilleur article à Medical Informatics Europe (MIE) 2006, Maastricht (The Netherlands)

Activité pédagogique

1. Présentation de l'activité d'enseignement

J'enseigne l'informatique au département Génie Industriel de l'INSA de Lyon, principalement en 3ème et 4ème année. J'enseigne les bases de l'informatique (architecture des ordinateurs et systèmes d'exploitation, XML, programmation VBA pour Excel) ainsi que ma spécialité de recherche à savoir l'Interaction Homme-Machine et design (IHM) que je coordonne pour le département. J'interviens également dans d'autres formations pour enseigner l'IHM comme le Mastère du département informatique de l'INSA de Lyon, le Master 2 informatique de l'Université Lyon 1 ou encore le Master 2 en sciences cognitives de Lyon 2. J'ai participé à la construction d'une UE conception centrée utilisateur dans le M2 santé, parcours ITEC de Lyon 1 (UE de 30h en cours de montage et qui a débuté en septembre 2023).

2. Présentation synthétique des enseignements

Enseignement	Diplôme	Formation	Nature	Effectifs	Volume
Interaction Humain-Machine	Ingénieur INSA	Initiale	Cours-TD, TP	Env. 100	30hTD, 28hTP
Architecture des ordinateurs et systèmes d'exploitation	Ingénieur INSA	Initiale	Cours-TD	Env. 100	49hTD
XML	Ingénieur INSA	Initiale	TD, TP	Env. 100	24hTD
Programmation VBA pour Excel	Ingénieur INSA	Initiale	TP	Env. 100	24hTD
Méthodologie d'analyse et de conception	Ingénieur INSA	Initiale	Cours-TD, TP	Env. 100	24hTD
Méthodologie de résolution de problème	Ingénieur INSA	Initiale	TP (serious game)	Env. 100	36hTD
Méthodologie de résolution de problème	Ingénieur Mastère INSA	Professionnelle	TP (serious game)	Env. 25	12hTD
Interaction Humain-Machine	Ingénieur Mastère INSA	Professionnelle	Cours-TD, TP	Env. 20	15hCM
IHMxIA	Universitaire M2 Lyon1	Initiale	CM, TP	Env. 25	1,5hCM + 3hTP
IHM pour sciences cognitives	Universitaire M2 Lyon 2	Initiale	CM	Env. 20	3hCM
Conception centrée utilisateur	Universitaire M2 santé ITEC Lyon1	Alternance	Cours-TD, TP	Env. 10	30hTD
Tutorat de projet collectif	Ingénieur INSA	Initiale	Encadrement	1/an	30hTD
Stages industriels	Ingénieur INSA	Initiale	Encadrement	3/an	14hTD
PFE	Ingénieur INSA	Initiale	Encadrement	3/an	14hTD

3. Responsabilités pédagogiques

Depuis 2020 : **coordination de l'initiation à la recherche documentaire** pour les élèves de 3ème année. Je suis l'interface entre les enseignants qui proposent les sujets de recherches, les étudiants (constitution des groupes, suivi des échéances, etc.) et les bibliothécaires qui assurent les TD et séances de tutorat.

Depuis 2021 : **Membre de l'équipe Mobilité Internationale** (IDI-OUT) du département Génie Industriel pour les départs à l'étranger des élèves de 4A. Mes missions sont d'accompagner les élèves de 4ème année dans leur projet de mobilité académique, assister aux commissions d'affectation des places à la DRI, valider les contrats d'études, suivre les étudiants pendant leur échange jusqu'à leur retour au département.

Activité scientifique

Encadrement doctorat et scientifique

1. Encadrement doctoral (2 en cours / 4 soutenues / 2 abondons)

- **Valentin MIDEZ** (12/2024 – présent), doctorant en informatique à l'Université Jean Moulin Lyon 3, sur le sujet « Analyse et visualisation de données physiologiques et comportementales pour favoriser la réflexivité en réalité virtuelle». Co-Encadrement (50%) avec Elise Lavoué (50%, Université Jean Moulin Lyon 3, Directrice). Financement : thèse financée sur le projet ANR RENFORCE.

- **Anthony BASILLE** (09/2021 – présent), doctorant en informatique à l'Université Jean Moulin Lyon 3, sur le sujet « Analyse de l'engagement et impact sur l'embodiment dans un jeu sérieux collaboratif ». Co-Encadrement (50%) avec Elise Lavoué (50%, Université Jean Moulin Lyon 3, Directrice). Financement : thèse financée sur projet du labex ASLAN.

- **Denis GUIBERT** (01/2020 – 06/2022), doctorant en informatique à l'Université Jean Moulin Lyon 3, sur le sujet « Analyse des comportements engagés des apprenants en vue d'une adaptation d'un jeu pédagogique ». Co-Encadrement (50%) avec Elise Lavoué (50%, Université Jean Moulin Lyon 3, Directrice). Financement : thèse CIFRE avec l'entreprise SCIADO Partenaires. *Abandon de la thèse pour des raisons de santé suite à un arrêt maladie longue durée (depuis octobre 2020).*

- **Delphine MULLER** (10/2020 – 03/2022), doctorante en informatique à l'Université Jean Moulin Lyon 3, sur le sujet « Ludification d'un environnement numérique d'apprentissage pour induire des changements de comportements du sommeil ». Co-Encadrement (30%) avec Elise Lavoué (40%, Université Jean Moulin Lyon 3, Directrice) et Amandine Rey (30%, Université Lyon 1). Financement : allocation doctorale CNRS. *Abandon de la thèse pour réorientation professionnelle.*

- **Stuart HALLIFAX** (03/2017 – 12/2020), doctorant en informatique à l'Université Jean Moulin Lyon 3 sur le sujet « Ludification adaptative de ressources pédagogiques numériques ». Thèse soutenue le 18 décembre 2020. Co-Encadrement (30%) avec Elise Lavoué (40%, Université Jean Moulin Lyon 3, Directrice) et Jean-Charles Marty (30%, LIRIS, Université Savoie Mont Blanc, Co-directeur). Financement e-FRAN (projet LudiMoodle) pour une durée de 3 ans. Aujourd'hui en poste dans l'industrie (Ubisoft Montréal).

- **Guillaume LOUP** (09/2014 – 12/2017), doctorant en informatique à l'Université du Maine, sur le sujet « Méthodes et outils pour des jeux pervasifs pour l'apprentissage ». Thèse soutenue le 4 décembre 2017. Co-encadrement (50%) avec Sébastien George du LIUM, Université du Maine (50%, Directeur). Financement ANR (projet JENLab). Aujourd'hui MCF Université d'Evry-Val d'Essonne.

- **Nam LY TUNG** (11/2013 – 10/2017), doctorant en informatique à l'Université de Würzburg (Allemagne), sur le sujet « Modélisation des comportements et des interactions dans un contexte d'assistance pour les personnes atteintes de la maladie d'Alzheimer ». Thèse soutenue le 18 octobre 2017. Co-encadrement (30%) avec Samir Aknine du LIRIS, Université de Lyon 1 (40%) et Prof. Jörn Hurtienne de l'Université de Würzburg (30%). Financement : allocation de doctorat de la Bayerische Forschungsstiftung pour une durée de 3 ans. Aujourd'hui en poste dans l'industrie.

- **Lili TONG** (10/2013 – 04/2017), doctorante en informatique à l'INSA de Lyon, sur le sujet « Designing and analyzing of collaborative activities in multi-surface environments». Thèse soutenue le 5 mai 2017. Co-encadrement (40%) avec Sébastien George du LIUM, Université du Maine (40%) et Youssef Amghar du LIRIS, INSA de Lyon (20%). Financement : allocation de doctorat du China Scholarship Council (programme de coopération CSC/UT-INSA) pour 3 ans ½. Aujourd'hui en poste dans l'industrie (BDO Global IT).

2. Encadrement Master / PFE / Stages ingénieur (10 M2 / 2PFE / 8 M1 / 5 DSAA)

- Victor OLIVA TORRES (2022-2023) : PFE du département Génie Électrique de l'INSA (GE). Co-encadré avec Élise Lavoué (Université Lyon 3) et financé sur le projet ANR RENFORCE.
- Florent DIET (2022-2023) : M2 ID3D de l'Université de Lyon 1. Co-encadré avec Élise Lavoué (Université Lyon 3) et financé sur le projet ANR RENFORCE.
- Jean BRIGNONNE (2022-2023) : M2R Informatique spécialité IADE (Intelligence Artificielle et Décision) de l'Université de Lyon 1. Co-encadré avec Diana Nurbakova (LIRIS, INSA Lyon) et financé par le LIRIS.
- Anthony BASILLE (2020-2021) : M2R Sciences Cognitives de l'Université de Lyon 2. Co-encadré avec Élise Lavoué (Université Lyon 3) et financé par le Labex ASLAN.
- Louis GUILLOTIN (2020-2021) : M2R Informatique spécialité IADE (Intelligence Artificielle et Décision) de l'Université de Lyon 1. Co-encadré avec Élise Lavoué (Université Lyon 3) et Benoit Encelle (Université Lyon 1) et financé par le Labex ASLAN.
- Sophie VILLENAVE (2020-2021) : PFE du département informatique de l'INSA (IF). Co-encadré avec Élise Lavoué (Université Lyon 3) et Guillaume Lavoué (LIRIS, ENI St Etienne) et financé par le LIRIS.
- Valentin LACHAND (2015-2016) : M2R Informatique spécialité IADE (Intelligence Artificielle et Décision) de l'Université de Lyon 1. Co-encadré avec Aurélien Tabard (LIRIS, Université de Lyon 1) et Jean-Charles Marty (LIRIS, Université de Savoie), en partenariat avec la start-up BIIN.
- Simon PAGEAUD (2014-2015), M2R Informatique Mobile et Répartie de l'UTBM (Université de Technologie de Belfort Montbéliard). Co-encadré avec Aurélien Tabard (LIRIS, Université de Lyon 1) et financé dans le cadre du projet de recherche ANR JENLab.
- David WAYNTAL (2014-2015), M2R Informatique spécialité IADE (Intelligence Artificielle et Décision) de l'Université de Lyon 1. Co-encadré avec Jean-Charles Marty (LIRIS, Université de Savoie) et Philippe Pernel (INSA Lyon).
- Carlos ALBERTO GOMEZ HERNANDEZ (2012-2013), M2R Informatique spécialité IADE (Intelligence Artificielle et Décision) de l'Université de Lyon 1. Co-encadré avec Yannick Prié (LINA, Université de Nantes) et financé dans le cadre du projet IXXI sur la co-adaptation homme-machine.
- Jonathan HERVAULT (2012-2013), M2R Informatique spécialité IADE (Intelligence Artificielle et Décision) de l'Université de Lyon 1. Co-encadré avec Sébastien George (LIRIS, INSA Lyon).
- Michael SCHUBERT (2010-2011), M2 Sciences Humaines et Sociales spécialité Sciences Cognitives de l'Université Lyon 2. Co-encadré avec Sébastien George (LIRIS, INSA Lyon).

8 encadrements de M1/ 4ème année ingénieur : Mehrnoosh VAHDAT (2012- 2013) ; Edouard BOUVET MARECHAL (2012-2013) ; Lisa COURANT (2015-2016) ; Estelle LEPEIGNEUX (2015-2016) ; Louis HASENFRATZ (2021-2022) ; Dorine VALLEIX (2021-2022) ; Marceau NAHON (2022-2023) ; Ngoc Minh NGO (2022-2023)

5 encadrements d'étudiantes du Diplôme Supérieur d'Arts Appliqués (DSAA) de Villefontaine : Clara Philippon (2016-2017), Emma Guttierrez (2020-2021) ; Anagaël Pereira (2020-2021), Elena Sonntag (2023-2024) ; Daniel Lalande (2023-2024)

3. Encadrement de postdocs et ingénieurs (3 postdocs / 3 ingénieurs)

- Nihal OUHERROU (2023-présent) : postdoc financée pour 2 ans sur le projet LUDIMOODLE+. Co-encadrée avec Élise Lavoué (LIRIS, Université Lyon 3)
- Anne-Laure GUINET (2023-présent) : postdoc financée pour 18 mois sur le projet TRANS3. Co-encadrée avec

Mathieu Loiseau (LIRIS, INSA Lyon)

- Yun ZHOU (2012-2013) : postdoc financée pour 12 mois par le projet de recherche Egonomy. Co-encadré avec Yannick Prié, LINA, Université de Nantes
- Leo VANBERVLIET (2023) : ingénieur pour 6 mois de financement sur le projet TRANS3. Co-encadrée avec Mathieu Loiseau (LIRIS, INSA Lyon)
- Joffrey MOUGEL (2018-2019) : ingénieur pour 9 mois Financement Pulsalys en collaboration avec la start-up SameSame. Co-encadrement avec Élise Lavoué (Université Lyon 3)
- Damien SORNETTE (2014) : ingénieur pour 4 mois de financement sur le projet Egonomy

Expertise

Membre de 5 jurys de thèse

- 2021 : Participation, en tant que membre externe, au jury de thèse de Mr Armel Ayimdji Tekemetieu, Université de Sherbrooke, Québec, Canada, spécialité « informatique », 10 novembre 2021.
- 2021 : Participation, en tant qu'examinatrice, au jury de thèse de Mme Reyhaneh Raissi, Sorbonne Université, spécialité « Sciences mécaniques, acoustique, électronique & robotique », 9 février 2021.
- 2017 : Participation, en tant qu'examinatrice, au jury de thèse de Mr Anthony FOULONNEAU, Université Grenoble Alpes, spécialité « Informatique », 12 décembre 2017 à Grenoble.
- 2017 : Participation, en tant qu'examinatrice, au jury de thèse de Mme Sara BOUZIT, Université Grenoble Alpes, spécialité « Informatique », 15 juin 2017 à Grenoble.
- 2014 : Participation, en tant d'examinateur, au jury de thèse de Mme Laure MARTINS-BALTAR, Grenoble INP, 25 septembre 2014 à Grenoble.

Participation à 5 jurys de M2 (hors établissement)

Participation à 8 comités de sélection de poste MCF

Évaluatrice d'appel à projets nationaux (ANR), régionaux (Région Nouvelle-Aquitaine) et internationaux (Canada)

Participation à des comités de programme et relectures

Comité de programme de conférence internationales : EC-TEL (2020,2024)

Comités de programme de conférences nationales : ERGO'IHM 2012 ; IHM (2011,2013,2014,2017,2018,2023,2024)

Relectrice pour les conférences internationales : EICS 2014; NordiCHI 2014; ISS 2016; INTERACT 2017; CHI-PLAY (2019,2021) ; EC-TEL (2021,2022,2023) ; CHI LBW 2022 ; CHI 2023 ; TEI 2023; MobileHCI 2024

Relectrice pour des revues internationales : Computer Graphics and Application (2019) ; IJHCS, International Journal of Human-Computer Studies (2020) ; International Journal of Human-Computer Interaction (2021) ; Journal on Multimodal User Interfaces (2021) ; Behaviour & Information Technology (2019) ; Plos One (2023)

Responsabilité dans l'organisation de conférences

2024 : Co-responsable de la catégorie Travaux en cours TEC IHM 2025
2020 : Co-responsable des ateliers et groupes de travail pour IHM 20-21
2019 : Co-responsable de la nuit des démonstrations pour IHM 2019
2017 : Co-responsable de la catégorie Travaux en cours TEC IHM 2017

2013 : Co-organisation des Rencontres Jeunes Chercheurs en IHM, juin 2013 à Lyon. http://rjc2013.afihm.org/
2011 : Responsable du comité d'organisation de l'école d'été internationale GBL 2011

Responsabilité dans l'organisation de journées d'étude, workshops

2021 : Organisation du Workshop GamLA@LAK21, LAK21, 12 avril 2021
2021 : Organisation de l'atelier GT#InteractionHybridation, conférence EIAH 21, 7 juin 2021
2017-2019 : Membre du comité de pilotage du GT EduIHM, IHM pour l'Education (https://eduihm.afihm.org/) Participation à l'organisation de 4 journées du GT lors des conférences IHM 2017, IHM 2018, EIAH 2019 et IHM 2019.
2016 : Participation au comité scientifique et à l'organisation de l'atelier « Interaction Homme-Machine pour l'éducation et la formation » pour IHM 2016, 25 octobre 2016, Fribourg, Suisse.
2015 : Co-responsable du comité scientifique et d'organisation de l'atelier « Méthodologies de conception collaboratives des EIAH : vers des approches pluridisciplinaires ? » pour EIAH 2015, 2 juin 2015 à Agadir, Maroc.
2011 : Organisation du workshop international sur « Supportive User Interfaces », SUI 2011, EICS 2011
2011 : Co-organisation de l'atelier « IHM avancées pour l'apprentissage » pour EIAH 2011 avec Sébastien George, 24 mai 2011, Mons, Belgique.

Projets de recherche

1. Coordination de projets de recherche

- **Labex ASLAN BODEGA** (2020-2024) : « Embodiment in collaborative serious games for soft skills training: impact study on engagement and alignment in gradual multimodal situations ». Co-coordinatrice du projet. Projet fortement interdisciplinaire (SHS et informatique), BODEGA se donne pour objectif d'étudier l'influence de l'incarnation sur les comportements sociaux et l'engagement des participants dans un jeu collaboratif conçu pour mesurer et/ou développer les capacités socio-relationnelles (soft skills). Partenaires : laboratoires LIRIS et ICAR, start-up SKILDER. Financement : 240K€. Co-encadrement d'un stagiaire de M2 sciences cognitives qui continue actuellement sur le projet comme doctorant (Anthony BASILLE). Web : http://icar.cnrs.fr/bodega/

- **Projet transverse LIRIS APAPS** (2022-2024) : « Adaptive and Privacy-Aware Persuasive Strategy for behaviour change». Co-coordinatrice du projet avec Diana Nurbakova (LIRIS-DRIM) et Antoine Boutet (CITI-PRIVATICS) Financement : 6K€, LIRIS. co-encadrement de plusieurs stagiaires (Jean BRIGNONNE, Ngoc Minh NGO)

- **ANR JENLAB** (2014-2018) : « Apprentissage avec les jeux épistémiques numériques : Usages – Technologies - Méthodologies ». Partenaires : S2HEP-EducTice (Lyon), ICAR (Lyon), LIUM (Le Mans-Laval), Symetrix (PME, Grenoble). Collaborations EPFL (Lausanne, Suisse) et U. de Madison-Wisconsin (USA). Financement : 525k€ dont 32k€ pour le LIRIS, Programme ANR Apprentissage 2013. Coordinatrice du projet (porteur) et responsable scientifique pour le LIRIS, responsable de lot (tâche 2 : Conception des dispositifs techno-pédagogiques et des situations d'apprentissages autour des JEN), gestion de projet et coordination, rédaction des rapports intermédiaire et final du projet, de livrables et co-encadrement d'une thèse (Guillaume LOUP), d'un stage de M2 (Simon PAGEAUD), et deux stages de 4ème année INSA (Estelle LEPEIGNEUX et Lise COURANT).

2. Responsable scientifique pour le LIRIS

- **ANR THERAPEUTIC** (2025-2029) : « Gamified incentivizing tangible interfaces for therapeutic patient education in the case of osteoporosis». Partenaires : les laboratoires de recherche publique LCOMS, PErSEUs, LIRIS et les Hôpitaux de Strasbourg (HUS). Financement : 825k€ dont 186k€ pour le LIRIS. Responsable scientifique pour le LIRIS. Travail prévu : co-encadrement d'un doctorant (à recruter) sur la gamification tangible adaptative dans des environnements hybrides.

- **PIA EGONOMY** (2012-2014) : « Navigation intuitive et personnalisée dans de très grandes bases de données images ». Partenaires : MOBEN FACT (Paris), la Réunion des Musées Nationaux (RMN, agence photographique), les PME PERTIMM, ART&FACT, XEDIX, TECDEV, les laboratoires de recherche publique CEA-LIST, LUTIN, et l'Institut de Recherche et d'Innovation du Centre Pompidou (IRI). Financement : 128k€ pour le LIRIS, Investissements d'Avenir (PIA 2011). Responsable scientifique pour le LIRIS, responsable de tâche (SP4.2 Analyse et exploitation de traces d'activités), rédaction de livrables et co-encadrement d'un postdoc (Yun ZHOU) et d'un ingénieur (Damien SORNETTE).

3. Participation à des projets de recherche

- **ANR RENFORCE** (2023-2026) : « Reflexive Multisensory Immersive Environment for ChemicalRisk Training ». Partenaires : laboratoires INL (CNRS), LIRIS-ORIGAMI (Centrale Lyon) et ECP (Université Lyon 2). Financement global : 651 K€. co-encadrement d'un doctorant (Valentin MIDEZ) et deux stagiaires (Florent DIET et Victor OLIVA TORRES). Web : https://renforce.projet.liris.cnrs.fr

- **ANR e-FRAN LudiMoodle+** (2023-2024) : Ludification adaptative pour la réussite des élèves. Partenaires académiques : Université de Lyon, Rectorat de l'académie de Lyon, Université Jean Moulin Lyon 3 (PAPN), Université Lumière Lyon 2 (ECP), INSA de Lyon (LIRIS), CNRS (LIRIS). Partenaire industriel : Pimenko. Financement total : 1 214 K€ (subvention : 622 k€), Appel à projets e-FRAN 3 (France 2030) - Territoires Éducatifs d'innovation numérique. co-encadrement d'une post-doctorante (Nihal OUHERROU). Web : https://ludimoodle.universite-lyon.fr

- **ANR ACCELER-IA** (2023-2027) : Adaptive Co-Construction of Ethics for LifElong tRrustworthy AI // Co-construction adaptative et pérenne de l'éthique pour une IA de confiance. Partenaires : LIRIS-CNRS UMR 5205, LIMOS UMR 6158 CNRS (Mines Saint-Etienne) // Confluence Sciences and Humanities Research Center -Lyon Catholic University (UCLy). Financement : 430399 €. co-encadrement d'un stagiaire (Marceau NAHON). Web : https://projet.liris.cnrs.fr/acceler-ai/

- **AMI Bien à l'école** (2023-2027) : Appel à Manifestation d'Intérêt Innovation dans la Forme Scolaire du PIA 4. Partenaires académiques : Académie de Lyon, Académie de la Réunion, Académie de Guyane, Académie de Guadeloupe, Académie de Martinique, Académie de Mayotte, Académie de Aix-Marseille, Académie d'Orléans-Tours, Laboratoire Icare, L'AFEV ; Partenaires industriels : porté par l'entreprise ProfessorBob.ai , SOFT KIDS, Kaligo LearnGo, Inschool (Cantoo), Didask, LearnEnjoy, Reverto, Spicee Educ, Short Edition, Beedeez, My-Serious-Game, Blended Learning, Antilogy, LDE, Synergie Family. Financement global :11,6 M€; dont 269 K€ pour le laboratoire LIRIS (CNRS). Travail prévu : co-encadrement d'un doctorant (en cours de recrutement). Web : https://bienalecole.fr

- **ANR eFran TRANS3** (2022-2025) : « Trois applications pour les apprentissages fondamentaux : Transmission de connaissances, Transfert labo-école, Transformations des pratiques ». Partenaires : Université Grenoble Alpes, Humans Matter, Les Editions Hatier, Région Académique de Mayotte, de Guyane, Rectorat de l'Académie de Grenoble, INSA Lyon, Université de Guyane. Financement global : 2 316K€ dont 378K€ pour le LIRIS. Participation aux travaux de recherche sur le jeu LUCIOLE, co-encadrement d'un ingénieur de recherche (Léo VANBERVLIET) et d'une post-doctorante (Anne-Laure GUINET). Web : https://trans3.cnrs.fr // https://trans3.cnrs.fr/luciole

- **PORTRAIT** financé par le LIRIS (2021-2022) : « Analyse des relations entre profil, comportement, et ressenti des joueurs en réalité virtuelle ». Partenaires : LIRIS, équipe ORIGAMI et ENISE. Financement : 20K€, LIRIS. Participation aux travaux de recherche (avec suivi de prestation) et co-encadrement d'un étudiant de l'INSA en stage.

- **CNRS LUDISOM** (2020-2022) : « Au dodo les ados ! La ludification d'un environnement numérique d'apprentissage au service d'un programme d'éducation au sommeil ». Partenaires : laboratoires CRNL et

HESPER (INSERM, Université Lyon 1). Financement CNRS AAP interdisciplinaire du défi “Processus et techniques d'apprentissage”: 8K€ + financement d’une allocation doctorale CNRS + financement de la fondation MAIF : 139840€. Participation aux travaux de recherche et co-encadrement d’une doctorante (Delphine MULLER).

- **Labex ASLAN VISITEURS** (2020-2021): « Video-based methods to Study International sTudents’ Experiences of the URban Space ». Partenaires : laboratoire ICAR. Financement : 6780€. Participation aux travaux de recherche et co-encadrement d’un stagiaire M2 informatique (Louis GUILLOTIN).

- **Projet transverse LIRIS** (2020-2022) : « Influence des caractéristiques de l’utilisateur sur la présence en réalité virtuelle – Vers un modèle de prédiction à partir des mesures physiologiques ». Partenaires : LIRIS, équipe ORIGAMI et ENISE - LTDS. Financement : 4850 €, LIRIS. Participation aux travaux de recherche et co-encadrement d’une étudiante de l’INSA en PFE (Sophie VILLENAVE).

- **eFRAN Ludimoodle** (2017-2020) : « Ludification adaptative des ressources pédagogiques numériques de Moodle comme levier de motivation des apprenants ». Partenaires : Université de Lyon (laboratoires LIRIS/Lyon 3 et ECP/Lyon 2, Université Lyon 3/PAPN), EDUNAO et Rectorat de Lyon. Financement total : 553 K€, Appel à projets e-FRAN 2016 - Programme d’Investissements d’Avenir (PIA). Participation aux travaux de recherche et co-encadrement d’un doctorant (Stuart HALLIFAX). Web : https://ludimoodle.universite-lyon.fr

- **Projets MAN et MAN2** (2015-2017) : Mise en place d’une méthodologie d’évaluation croisée de l’accès aux ressources numériques. Partenaires : LIRMM, IRIT, LAAS, LERASS, CERTOP, CLLE, LIRIS, BMBI, Handibio, MICA, INRIA et LPNC. Projet financé dans le cadre des Défis CNRS AUTON. Participation aux réunions et travaux de recherche.

- **FUI SEGAREM** (janv. 2010-déc. 2012) : « Serious Games en Réalité Mixte». Partenaires industriels : Symetrix, Total Immersion. Financement : FUI, DGCIS. Participation au projet (conception et évaluation du prototype).

- **APPSGATE** (sept. 2012-fév. 2015) : « AppsGate Application Gateway ». Partenaires : LIG (Grenoble), PACE, Technicolor, NXP, 4Mod, ARD, Immotronic, RippleMotion Simon tech VideoStream Network, SoftKinetic, Vestel, Telecom ParisTech. Financement : projet européen EUREKA-CATRENE CA 110. Participation au projet en tant que consultante externe sur les aspects analyse des besoins, programmation par l’utilisateur final et assistance.

Collaborations internationales

2019 : Collaboration avec l’Université de Waterloo / HCI Game Group au Canada, par le biais d’un séjour de 2 mois d’un doctorant (Stuart HALLIFAX)
2017 : Collaboration avec l’Université de Southampton et le LIRIS (équipe SICAL et GRAMA) avec l’accueil de Dr Sarvapali RAMCHURN, associate professor à Southampton, comme chercheur invité INSA pendant 1 mois (mars 2017) sur le thème de la « Modélisation des interactions usagers-systèmes intelligents ». Organisation de séminaires et échanges sur différents projets de recherche pendant cette période.
2013-2017 : Collaboration avec des chercheurs de l'Institut d'Interaction Homme-Machine et Medias de l'Université de Würzburg en Allemagne autour de la conception de systèmes d'assistance pour les personnes en perte d'autonomie. Plusieurs actions ont été menées dans ce cadre, dont le co-encadrement de la thèse de Nam Ly Tung d’octobre 2013 à octobre 2017, visite de l'Institut d'Interaction Homme-Machine et Medias de l'Université de Würzburg en octobre 2017 et rédaction d’articles communs.

Séminaires, conférences invitées et présentations

2022 : Interview diffusée sur les réseaux sociaux à l’occasion de la Journée Internationale des femmes et filles de sciences 2022 dans le cadre d’une campagne de communication #DreamItBelt, conjointe à l’ensemble des projets européens portant sur l’égalité // Journée de la femme en science (ANR)

2021 : Présentation « La ludification adaptative pour motiver les élèves : Résultats et recommandations pratiques. » avec Stéphanie Reyssier + Participation à la table ronde « La ludification des contenus pédagogiques : une démarche collaborative et itérative » lors de la Journée scientifique LUDIMOODLE : « Etat des lieux et prospectives. La ludification comme levier de motivation des élèves », le 15 novembre 2021.
2021 : Séminaire invité « Design, Engagement utilisateur, Gamification », Audrey Serna et Elise Lavoué, à la matinale de EdTech Lyon, 12 janvier 2020
2019 : Invitée à une table ronde « L'intégration d'un environnement ludique dans les pratiques enseignantes dans un processus de généralisation », séminaire organisé dans le cadre du projet LudiMoodle 28 juin 2019
2019 : Animation de la table ronde « Scénarisation et design ludique : comment engager et motiver les apprenants ? », séminaire académique « Ludification des apprentissages » organisé par la DANE LYON, 24 décembre 2019 à St Etienne
2016 : « Mobile, Tactile and social technologies for learning », Christine Michel et Audrey Serna, Université de Lyon pour le French corner @ EC-TEL 2016, dans le cadre du réseau ANR ORPHEE, 13 septembre 2016, Lyon.
2014: Séminaire invité « Interaction située, modularité, apprentissage » au LIG, le 26 juin 2014 à Grenoble.
2014 : Conférence invitée « Espaces d'interaction modulaires » à FITG 2014 (Forum sur l'Interaction Tactile et Gestuelle) organisé par l'INRIA de Lille, les 13-14 juin 2014. http://fitg.lille.inria.fr/exposes/
vidéo :http://acfx.fr/fitg/videos/1_AudreySerna.mp4
2011 : Conférence invitée « Quelques exemples de projets de recherche impliquant chercheurs en sciences cognitives et chercheurs en informatique » pour la journée « sciences cognitives et informatique », organisée par le LIRIS le 10 mai 2011 à Lyon. http://liris.cnrs.fr/evenements/recherches-en-sciences-cognitives
2011 : Séminaire invité « Favoriser l'autonomie de l'utilisateur dans les environnements interactifs: Vers la conception de systèmes d'assistance cognitive » dans le cadre de projets PAL de l'INRIA de Grenoble, le 18/04/2011

Détail des responsabilités scientifiques

- **Depuis 2019** : **Responsable d'équipe adjointe de l'équipe SICAL** (https://liris.cnrs.fr/equipe/sical) : L'équipe SICAL de laboratoire LIRIS propose des approches, modèles et outils génériques pour améliorer la capacité de l'humain à interagir, apprendre et s'adapter dans un contexte collaboratif. SICAL s'intéresse particulièrement à l'interaction en tant que phénomène socio-technique où utilisateur et système co-évoluent. Effectifs : 8 enseignants-chercheurs, 1 chargé de recherche, 1 émérite. Actuellement : 6 doctorants, 1 post-doctorant, 2 ingénieurs d'étude. Budget (fonctionnement interne au laboratoire) : environ 4000€/an.

- **2020-2025** : **Membre du comité de pilotage du Labex ASLAN** (https://aslan.universite-lyon.fr), co-responsable du WorkPackage « language in society » : gestion d'un budget d'environ 22k€/an pour le financement des demandes de projets « au fil de l'eau » des partenaires du Labex. En tant que responsable de WP, nous assistons à tous les comités de pilotage du labex (1 par trimestre environ), et nous gérons les demandes de financement des membres du Labex (réception, étude et validation des dossiers).

- **Depuis 2020** : **Membre du comité de suivi des doctorants du LIRIS**, école doctorale InfoMaths 512. Chaque doctorant du laboratoire est suivi par un membre interne de l'école doctorale. Une réunion de suivi de thèse est organisée par an entre le doctorant, ses encadrants, le membre interne de l'ED et l'expert externe. En tant que membre interne de l'ED, nous sommes chargés d'écrire un rapport après chaque réunion de suivi. Suivi de : Axel Paris (équipe ORIGAMI), Julien Lacombe (équipe ORIGAMI), Clément Lemeunier (équipe ORIGAMI), Mathieu François (équipe IMAGINE).

- **2022-2020** : **2 ans Présidente référente du comité d'évaluation ANR CE33 « Interaction, robotique »; 1 an Vice-Présidente et 1 an membre.** Pour évaluer les projets soumis à l'Appel à Projets Générique de l'ANR. En tant que présidente référente, mon rôle est d'assister aux formations dispensées par l'ANR, constituer le comité (sélection des membres du comité), affecter les portefeuilles de chaque membre, animer les réunions plénières en étape 1 et 2, valider les rapports post-comité avant envoi aux coordinateurs de

projets, assister aux comités spécifiques (IA et SHS par exemple pour le CE33).

- **2020-2022** : **Co-porteuse du groupe de travail de la DNE** #GTNUM#interactionhybridation dans le cadre du « GTnum 2 : Enseignement et apprentissage en situation hybride présentiel/distanciel : vers une réinvention de la forme scolaire ?» financé par la Direction du numérique pour l'Éducation (DNE), bureau TN2 chargé du soutien à l'innovation numérique et à la recherche appliquée, du ministère de l'éducation nationale et de la jeuneuse pour une durée de 2 ans et un financement de 50k€. Porteurs : Laboratoire PERSEUS de l'Université de Lorraine et laboratoire LIRIS / INSA Lyon.

Part II.

Scientific Report

1. Introduction

1.1. Academic context of my research

The environments I studied emerged from collaboration opportunities, synergies with colleagues, and various projects. My investigation into how technology could support autonomy for people with cognitive disorders began during my PhD at DOMUS and TIMC-IMAG labs. I worked on a user model to be integrated into an intelligent system, which would model the progressive decline of cognitive processes, allowing the system to better adapt.

Following my PhD, I joined the LIG-IIHM research group in Human Computer Interaction (HCI) as a postdoc, where I worked on User Interfaces (UI) plasticity. I was particularly interested in how an interactive system can be adapted to the context of use, specifically focusing on users' profiles and behaviors, and exploring the distribution of UI across several devices.

Subsequently, I was recruited by INSA Lyon as an associate professor at the LIRIS lab, in the Situated Interaction, Collaboration, Adaptation, Learning (SICAL) research group, which predominantly focuses on Education and Technology Enhanced Learning. Here, I began investigating how distributed technologies (multi-device environments) and immersive games could enhance learning and collaborative processes. Concurrently, I explored gamified environments and, more recently, hybrid environments that combine physical and digital devices.

Since then, my research has particularly focused on how technologies impact motivation and engagement, and more broadly, User eXperience (UX). I aim to leverage this knowledge to design adaptive or tailored interactive systems.

1.2. Research question overview

I'm interested in understanding more thoroughly how users can be supported in interacting in multi-devices, immersive, gamified or hybrid environments. This involves dealing with complexity and addressing non-instrumental needs.

Certain parts of that question are commonly addressed and investigated through the lens of UX in the HCI research.

Beyond instrumental aspects, researchers have started considering non-instrumental human needs or values as an integral part of technology acceptance and judgment on the quality of interactive systems. In the 2000s, different works argued that technologies should support values such as hedonic aspects [Hassenzahl et al., 2000], pleasure [Jordan, 2002], intimacy, diversion, and ludic values [Gaver and Martin, 2000]. In 2003, Hassenzahl proposed a model of user experience in which he distinguishes pragmatic aspects related to the

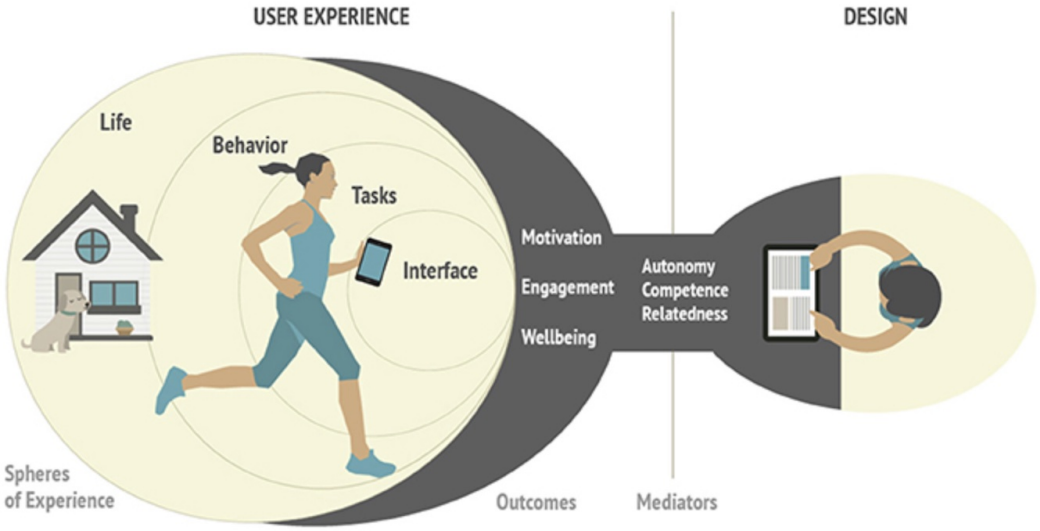


Figure 1.1.: METUX model taken from [Peters et al., 2018] defines four spheres of experience and articulates the three basic psychological needs of SDT.

fulfillment of users' behavioral goals from hedonic attributes that emphasize individuals' psychological well-being. He defines three hedonic functions of products: stimulation (i.e., supporting personal development and increasing knowledge and skills), identification (i.e., communicating identity to others and self-expression), and evocation (i.e., provoking valued memories). Pursuing this trend, some researchers have proposed to encompass these aspects into new ways of considering design, notably Cockton's proposition of value-centered HCI [Cockton, 2004] or Norman's emotional design [Norman, 2004]. Both researchers argue that interaction should be affective and emotional. Finally, in their research agenda for UX, Hassenzahl and Tractinsky [2006] define three facets of UX: 1) beyond the instrumental including holistic and hedonic aspects; 2) emotion and affect which are subjective and positive; 3) the experiential which focuses on the use of technology creating situated, dynamic, temporally bounded experience. They also insist on the positive emotional outcomes of UX and argue that *"UX in the sense of a positive HCI would, thus, focus on how to create outstanding quality experiences rather than merely preventing usability problems."*

More recently, shaping positive and flourishing user experiences, supporting well-being [Peters et al., 2018] or designing meaningful and engaging situations [Nacke, 2017] have gained growing interest. Paradigms grounded on positive psychology theories propose to integrate psychological factors into design strategies. Positive Technology [Riva et al., 2012; Zhang, 2007] and Positive Computing [Calvo and Peters, 2014] promote technologies that support psychological well-being and human potential. These approaches rely particularly on theories about motivation, engagement, and flow [Czikszentmihalyi, 1990]. Among these, the Self-Determination Theory SDT [Ryan and Deci, 2000b, 2017] offers a well-established framework that identifies three basic psychological needs (autonomy, competence, and relatedness) essential to people's self-motivation and well-being. Autonomy is highly connected to meaning and purpose, and corresponds to the feeling of agency, willingness, and volition in acting. Competence means feeling able and effective. Relatedness corresponds to the sense of belonging and feeling connected with others. In their approach for designing for motivation, engagement, and thriving, Peters et al. [2018] argue that considering these three

basic needs through the design of functions, features, and contents of technologies, and their evaluation can improve user experience. They propose a model (METUX) that differentiates different spheres of experience within which technology can influence well-being at different levels called spheres (interface, task, behavior, and life spheres), as shown in Figure 1.1. SDT has become one of the most widely applied theories on motivation in HCI research, as demonstrated by the recent workshop aiming at establishing a research agenda on the use of SDT in HCI held at CHI 2022 [Ballou et al., 2022].

These design considerations can be studied through the lens of affordances. The term *affordance* is commonly used to describe the real or perceived properties that determine how artifacts can potentially be used. First introduced by Gibson in the field of ecological psychology [Gibson, 1979], the concept has been popularized in the HCI community thanks to Norman's work [Norman, 1988, 1999]. Gibson's definition emphasizes the objective properties of the environment that directly inform users about possible actions, while Norman's concept of perceived affordances acknowledges the subjective interpretations and mental models of users, influenced by their experiences and cultural backgrounds. Building upon these approaches, Gaver [1991] focuses on affordances of software applications. He operationalizes the design by proposing to consider separately the affordances from the information available about them, which specify the affordances. According to him, considering affordances in the design encourages devices and technologies to be considered in terms of the actions they enable, focusing on the fundamental interactions between technologies and users. Since then, researchers have considered this concept to evaluate and guide the design of artifacts providing affordances that align with users' expectations to create relevant user experiences [McGrenere and Ho, 2000].

Embracing this line of research, I investigate how interactive systems should be designed to provide properties, functionalities, and affordances grounded in psychological theories that will support users in their activities, creating meaningful and adapted experiences, fostering motivation and sustained engagement.

1.3. Challenges Related to the Environments Studied

One of the strengths of SDT is its applicability to real-life domains such as education, health care, work, video games and virtual environments [Ryan and Deci, 2017], which echo the contexts in which I conducted my research. These contexts can be divided into three broad categories, each raising issues and challenges related to UX and requiring design approaches grounded in psychological theories and frameworks.

1.3.1. Multi-Devices Environments

In multi-device environments, the combination of devices raises opportunities, reconfiguring the relationship between people, objects, and space [Williams et al., 2005]. As underlined by the authors, social actions are tightly related to the concept of space. The spatial organization of activities makes them "seeable" and intelligible to others, allowing people to collectively act in space and achieve concerted social action. Hornecker and Buur [2006]

underline that *there is a need for principled approaches supporting research and design of these new hybrid environments that are inherently 'socially-organized settings'.* Therefore, multi-device environments offer affordances for social interaction, allowing multiple users to interact in the same space, aiming at collaborative activities or cooperative scenarios.

In the field of education, interactive displays and tabletops have gained interest for collaborative learning settings (Computer Supported Collaborative Learning (CSCL)), giving importance to face-to-face collaboration and acknowledging the physicality of learning [Dillenbourg and Evans, 2011]. In the same line, Yuill and Rogers [2012] underline that multi-user interfaces extend the possibilities for communication and collaboration thanks to parallel action of touching, mobility of users, and increased ability for natural expressions of behavior such as gesture and posture. I am thus particularly interested in multi-devices environments composed of several interactive surfaces, called multi-surfaces environments (Multi Surface Environment (MSE)) since they are well suited for problem solving activities with multiple solutions and the exploration of rich data.

Despite the opportunities of such environments, Zhang et al. [2021] underline that the experience in multi-device environments is far from satisfactory, facing several challenges related to cross-device interaction. They identify problems that degrade the experience, such as differences in operating systems and user interfaces, poor ability for data sharing, unclear coordination, pairwise interactions, or lack of understanding intent. They argue that more research should be done to better understand the factors affecting UX in multi-device scenarios and to propose models, methodologies, and tools for multi-device UX design. In particular, they underline the need to support the feelings of control, autonomy, competence, and relatedness, referring to the SDT. In addition, Yuill and Rogers [2012] identified mechanisms accounting for the success of multi-user interfaces for collaboration that should guide the design of such technology, including high awareness of others' actions and intentions and high availability of background information.

Thus, there are still open questions regarding how to support effective collaboration and user experience in MSE.

1.3.2. Immersive learning environments and games

Immersive technology is defined as *a technology that blurs the boundary between the physical and virtual worlds and enables users to experience a sense of immersion* [Suh and Prophet, 2018]. From their literature review, the authors identified the positive impact of immersive technologies on learning experiences, participation in collaborative activities, and engagement. Immersion can be achieved thanks to multi-sensory stimulation as defined by Slater [2009], with technologies such as Virtual Reality (VR), Augmented Reality (AR), or Mixed Reality (MR), but can also be considered as a psychological state according to Agrawal et al. [2020]. These technological environments are often combined with approaches that promote cognitive immersion, such as game-based or role-playing methods [Marocco et al., 2015; Checa and Bustillo, 2020] to promote active learning and engagement. Despite their potential, many studies show that to be effective, these environments should consider several psychological issues such as the levels of immersion, presence, flow, or engagement [De Freitas et al., 2010]. For Oh et al. [2018], the level of immersion can be directly measured by the technological affordances. Thus, some authors underline the lack of empirical research that explains systematically how and why these immersive technologies impact user experience and performance [Suh and Prophet, 2018].

In the field of games, these considerations are usually studied through the lens of "player experience," a concept refined from UX resulting from the combination of HCI and Game Development research [Nacke, 2017; Vanden Abeele et al., 2020]. Player experience is defined as the individual and personal experience of playing games and is typically investigated during and after the interaction with games [Wiemeyer et al., 2016]. Player experience usually relies on generic psychological models, such as SDT (e.g., Player Experience of Need Satisfaction (PENS) [Ryan et al., 2006]), flow, presence, and immersion [Wiemeyer et al., 2016]. Tyack and Mekler [2020] underline a lack of explicit considerations of SDT concepts and propose a research agenda on how SDT should be used in the field of games. Recently, Vanden Abeele et al. [2020] proposed a new instrument, the Player eXperience Inventory (PXI), to measure player experience and help understand how players perceive low-level game design choices and how these contribute to higher-order psychological experiences, including meaning and immersion. Thus, they also emphasize the importance of understanding how design choices and game features affect UX.

Whether in the field of games or immersive environments, researchers all stress the need to draw on theories in order to better understand how technology affordances and features influence perceptions of UX to inform the design of such technology, including concepts of immersion, flow, presence, engagement, and motivation.

1.3.3. Gamified environments

Gamification is defined as *"the use of design elements characteristic of games in non-game contexts"* (such as points, badges, leaderboards, etc.) [Deterding et al., 2011]. Over the last decade, gamification has been widely integrated into learning environments as a way to stimulate learners' motivation and user experience as shown in recent systematic reviews on gamification within the educational domain [Dicheva et al., 2015; Subhash and Cudney, 2018; Zainuddin et al., 2020a; Sailer and Homner, 2020; Briffa et al., 2020], as well as for health [Jia et al., 2016; Orji et al., 2017b] and the workplace [Oprescu et al., 2014]. These meta-analyses identify empirical studies that investigate the effects of gamification mostly on learners' motivation, engagement, and performance. The results of these studies tend to show positive effects [Subhash and Cudney, 2018; Zainuddin et al., 2020a; Briffa et al., 2020]. Zainuddin et al. [2020a] particularly underlines the importance and the role of engagement in learning outcomes, as they observe that values of engagement and motivation were always positively correlated with academic performance.

These reviews also underline that SDT is the most frequently used theoretical framework to support the design of game elements [Seaborn and Fels, 2015b; Zainuddin et al., 2020b], focusing especially on the integration of need satisfaction into design guidelines [Deterding, 2015; van Roy and Zaman, 2017]. SDT and need satisfaction are also used to assess the impact of gamification on motivation, observing positive results such as those found by [Sailer et al., 2017; van Roy and Zaman, 2018; Xi and Hamari, 2019]. However, several studies have found contradictory or mixed results, showing that users can be more or less receptive to different game elements [Busch et al., 2015; Kaptein et al., 2012; Orji et al., 2013; Monterrat et al., 2015, 2017; Mekler et al., 2017]. Sailer and Homner [2020] show that results on motivational and behavioral learning outcomes cannot be interpreted as stable due to different factors.

First, some authors underline the need for gamification to be meaningful in order to obtain positive impacts. Nicholson [2015] defines meaningful gamification as *the use of gameful and playful layers to help a user find personal connections that motivate engagement with a specific*

context for long-term change. Second, Van Roy and Zaman [2019] underline that situational factors can shape feelings of autonomy, competence, and relatedness differently. This importance of the context was already underlined by Deterding [2011] when designing successful gamification. The author introduced the concept of *situated motivational affordances* to conceptualize the motivational pull of game design elements in varying contexts. Third, several of these studies point out the fact that the impact of gamification depends on individual factors, such as user personality, player profile, and game preferences [Orji et al., 2017b; Lopez and Tucker, 2018; Monterrat et al., 2017] or even learners' motivation for the learning task [Lavoué et al., 2019; Bennani et al., 2021]. Thus, these environments should consider users' characteristics when designing motivational affordances. Finally, motivation and engagement may fluctuate over time. Klock et al. [2020] underline the importance of considering the dynamic and cyclical nature of gamification to improve user experience in the long term. They highly recommend investigating *"how users may change from time to time and how interaction evolves"* to periodically update these dynamic models. This need for a deeper understanding of users' experiences is also highlighted by other meta-analyses [Rodrigues et al., 2021b; Oliveira et al., 2022b].

These factors raise challenges in designing meaningful, adapted gamification to support motivation and sustained engagement.

1.4. Toward meaningful and adapted experience for sustained engagement

Considering the challenges raised by these different environments, my research focuses on the following specific facets that interactive systems should integrate.

1. Fostering motivation and sustained engagement with technology.

Fostering motivation and sustained engagement is a central preoccupation when designing technologies for supporting well-being, as already underlined [Nacke, 2017; Peters et al., 2018]. The two concepts are closely related, and each one influences the other. Most of the time, motivation is considered as an intent (internal state) whereas engagement is an action (observable behavior) [Reschly and Christenson, 2012], which can be considered as an outcome of motivational processes [Reeve, 2012]. Motivation is driven by intrinsic and varied extrinsic sources and impacts cognitive and social development, importantly influencing individual differences [Ryan and Deci, 2017]. Engagement can be seen as the quality of user experience [O'Brien and Toms, 2008], the level of involvement in an activity or a game [Brown and Cairns, 2004], or the shift of attention towards an activity to achieve specific objectives [Bouvier et al., 2014a]. In the field of education, engagement is considered as a complex and multidimensional process distinguishing three complementary dimensions: cognitive, motivational (or affective), and behavioral engagement [Linnenbrink and Pintrich, 2003; Fredricks et al., 2004].

Whatever the definition, the fluctuation of motivation and engagement over time is an important challenge to address. Hassenzahl and Tractinsky [2006] insist on the importance of considering the temporal and dynamic aspect of experience. Regarding engagement,

O'Brien and Toms [2008] distinguish points of engagement and disengagement that create a dynamic process. Disengagement can be caused either by internal or external factors. They identify internal factors such as lost interest, feeling of pressure associated with the opinions of others, time, or other tasks. External factors consist of distractions and interruptions, lack of novelty in the application, and usability issues with the technology. In the field of gamification, several longitudinal studies reported a decrease in engagement or performance in the long run [Hanus and Fox, 2015; Sanchez et al., 2020; Rodrigues et al., 2022a]. One potential explanation is that the novelty effect could lead to positive effects of gamification that do not necessarily continue over time [Seaborn and Fels, 2015a; Hamari et al., 2014; Koivisto and Hamari, 2019].

To sum up, there are important individual differences regarding motivation Ryan and Deci [2017], and as underlined by Perski et al. [2017], *engagement is considered to be a dynamic process that is expected to vary both within and across individuals over time.* Therefore, it is necessary to create meaningful experiences adapted to individuals and to the context to foster motivation and sustained engagement.

2. Supporting meaningful experience and interaction.

Users should be supported in their activities while using interactive systems by creating meaningful and outstanding quality experiences, as argued by Hassenzahl and Tractinsky [2006]. This echoes the SDT which considers that people who are intrinsically motivated by purpose and meaning will engage in activities. In UX, different works underline the importance of meaning in using technology by distinguishing hedonic aspects from eudaimonic ones [Desmet and Hassenzahl, 2012; Mekler and Hornbæk, 2016]. According to their literature review, Mekler and Hornbæk [2016] suggest that hedonic UX appeals to momentary pleasures directly derived from technology use, whereas eudaimonic UX is about striving towards and accomplishing personal goals through technology use, with increased need fulfillment, positive affect, meaning, and long-term importance. Desmet and Hassenzahl [2012] insist on the importance of identifying meaningful life goals since they provide direction by connecting abstract values, such as being autonomous or feeling related, to everyday activities. Some studies have shown that prolonged experience with technology is tied to how it becomes meaningful in users' lives [Karapanos et al., 2009]. Thus, the authors promote designing for meaningful mediation, daily rituals, and the self to favor long-term engagement. Several other works integrate the notion of meaningful experience in the design of technology, such as [Höök, 2004; Tan and Chow, 2017; Hodge et al., 2019]. Recently, Woźniak et al. [2023] developed a scale to measure the eudaimonic properties of technologies. They suggest that it can be used at the early stages of the design process to rapidly compare prototypes and identify more optimal design versions.

Integrating meaningful experiences into the design of technologies can take various forms and affordances. As well explained in their approach, Peters et al. [2018] stated that *"beyond the sphere of the user interface, technologies can also facilitate greater autonomy within daily life by removing obstacles or augmenting capabilities, allowing people to pursue self-determined goals more fluently."* They gave the example of assistive technologies or health management apps, which can increase autonomy in relation to daily behaviors. In gamified environments, several works argue that gamification should be meaningful to users, by connecting an experience to previously-held beliefs [Nicholson, 2015] or resonating with what is important

[Vanden Abeele et al., 2020] to engage users in the long term. Design and evaluation methods started to integrate this dimension, such as [Deterding, 2015; Vanden Abeele et al., 2020]. Nicholson [2015] underline that creating something meaningful is highly dependent on each individual and their past. He states that "*a designer of a meaningful gamification system will have to provide a variety of experiences and ways of engaging to raise the chances that each participant can find something meaningful*".

3. Providing adapted experience.

Most UX definitions underline the subjective aspect of experience, in particular Hassenzahl [2003] that insists on the fact that experiences may differ between individuals (due to personal standards) but they also vary between situations and change over time. Personalizing technology to individuals can reinforce the sense of ownership and choice and can have positive effects on motivation, in particular on the sense of autonomy [Ryan et al., 2006]. Thus, adapting technology should tackle challenges related to individual aspects of UX, but also to its dynamic and situated aspects. The literature on adaptive systems usually distinguishes two approaches: static adaptation occurring at the system initialization and dynamic adaptation at runtime [Calvary et al., 2003, 2011].

Static (tailored) approach: The adaptation of technology can be done when initialising the system. This approach is particularly used to tailor or personalize features to users' profiles. The system will propose features relevant to users' characteristics once the user has completed their profile. This supposes that this tailored approach has been integrated at the design stage, embedding in the design methods and tools to characterize and understand the users' characteristics and motivation. In the field of games and gamification, this approach has gained interest since several works argue that not everyone shares the same interests, preferences or motivation and thus that game elements should be tailored to users [Böckle et al., 2017; Rapp et al., 2019]. Several systematic literature reviews [Hallifax et al., 2019b; Klock et al., 2020; Oliveira et al., 2022b] have shown that tailored gamification studies have mainly adopted a static approach, by exploring ways to model the user profile to take into account users' inter-individual differences [Bennani et al., 2022]. These studies mainly rely on statistical methods, adaptation rules or data-mining methods [Klock et al., 2020].

Dynamic approach: The adaptation is performed during the use of the system, leading to dynamic adaptation. This approach implies more complex architecture than static adaptation, including the recognition of the situation, computation of a reaction, and execution of the reaction [Calvary et al., 2003]. The recognition of the situation includes first sensing the context (device composition, users' behaviors, emotions, etc.) and then detecting and identifying context changes before triggering the adaptation algorithms. For instance, Alipour et al. [2023] propose a framework for adapting UI to emotions, consisting of a sensor engine, an inference engine, and an adaptation engine. From the user perspective, dynamic adaptation also raises challenges in terms of intelligibility, explainability, and controllability to be understood and accepted by users [Abdul et al., 2018]. Works, such as García Frey et al. [2010], propose to include self-explanatory properties directly into user interfaces. In multi-device environments, the potential reconfiguration of devices or spatial arrangement of people creates dynamic transitions that can be taken into consideration as changes of context. Some studies use this information to propose proxemics and micro-mobility interactions to let users manage dynamic adaptation [Marquardt et al., 2012]. In the field of

positive computing, some works propose models based on interaction to adapt goals and motivational messages in a dynamic way using the history of performances [Rei et al., 2022, 2024]. Regarding gamification, dynamic adaptation is identified as a promising research avenue for future work in gamification [Klock et al., 2020; Oliveira et al., 2022b], raising challenges related to tracking users' interactions and analyzing and monitoring their behaviors, in particular the detection of engagement or motivation decrease.

1.5. Research axes

Designing interactive systems that foster meaningful, engaging user experience, supporting interaction and providing adapted experience raise several issues, questioning and avenues for research. I distinguish three strongly interrelated research axes, each one raising several challenges that I will address in the different chapters of this manuscript.

Research Axis 1

Observing and understanding users' activities and experiences with technology to inform the design.

To support meaningful experience and interaction, the first axis aims at improving our understanding of how users conduct activities with technology and how it impacts their behaviors and experience. I investigate external factors that will influence experience, such as the context or the affordances of technology. I am particularly interested in analyzing how different designs, devices or interactions, support users in their activities and how it shapes their behaviors. I rely both on empirical approaches by conducting situated studies and on theoretical frameworks to guide the analysis of users' behaviors, as illustrated in Figure 1.2. The two approaches are complementary and build on each other. [Rogers, 2004] distinguishes several purposes of theories in HCI, including : explanatory (explicating relationships and processes), predictive (enabling predictions to be made about user performance) or prescriptive (providing guidance for design). This is in line with Hekler et al. [2013], who underline that theories are usually used to inform the design of technical systems and to guide evaluation strategies. However, sometimes the theories are insufficient to guide concrete design and *empirical findings can yield concrete and contextually-specific findings, which can be applied to ground specific designs and to create design guidelines*.

The contributions are mainly empirical by providing findings from situated and laboratory studies, and methodological with the proposition of methods and models to analyse users' activities, experience and behaviors.

Research Axis 2

Modeling users' characteristics, activities and experiences.

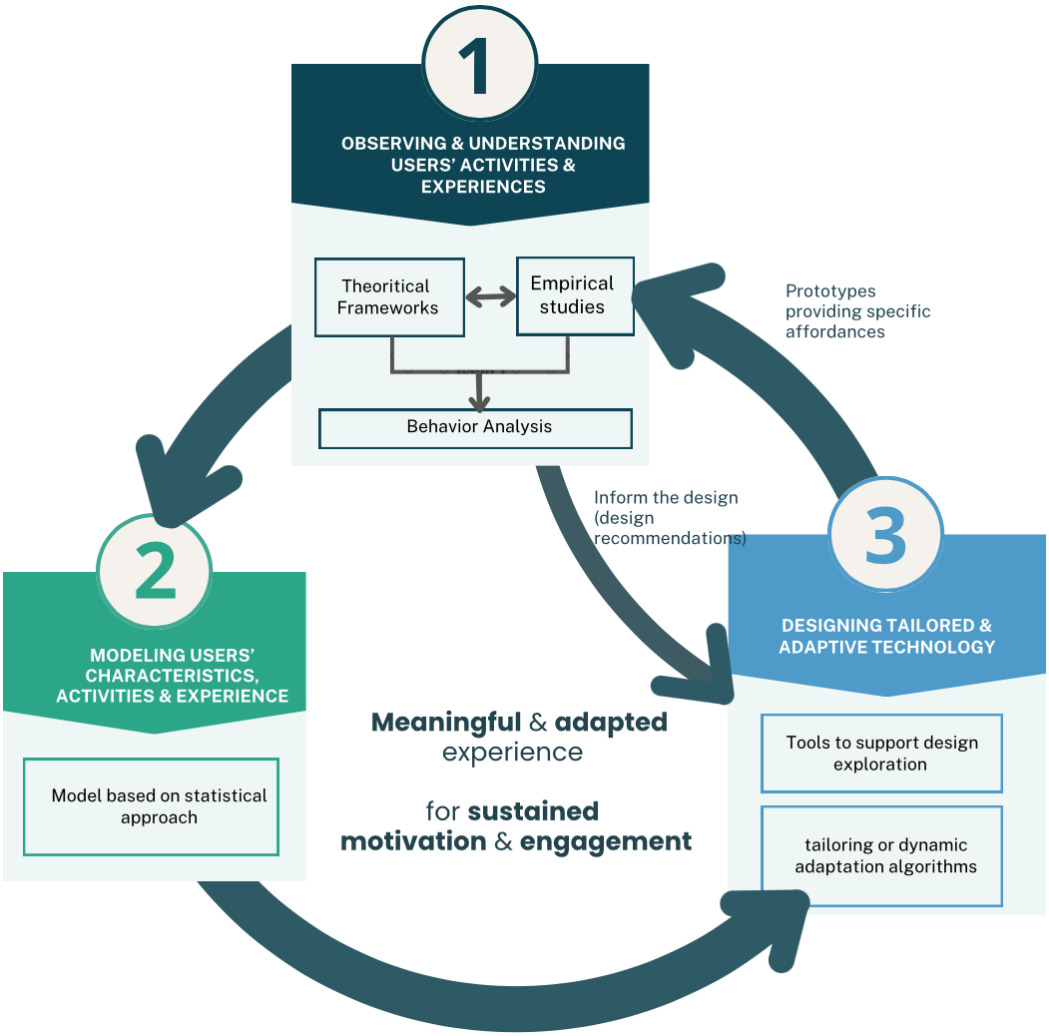


Figure 1.2.: Articulation of my research question and the three research axes, highlighting the different contributions.

To be able to provide meaningful and adapted experiences, it is necessary to take into account different aspects of the context of use. Usually, in the field of context-aware computing and adaptive UI, the context of use includes both environmental and technical aspects related to the devices used and the users' characteristics [Calvary et al., 2003; Alipour et al., 2023]. In my research, I am particularly interested in investigating the individual factors that influence users' experience or behaviors, such as users' preferences or characteristics. The aim is to build users models that will then serve to adaptation, which constitutes my last research axis.

The contributions are mainly empirical in identifying relevant users' characteristics to consider in the modeling process, and methodological with the use of statistical approaches to model the influences of these characteristics on UX.

Research Axis 3

Designing tailored or adaptive technology.

This last axis focuses on developing tools to design technology that supports meaningful and adapted experiences, fostering motivation and sustained engagement. This includes tools to guide the design of interaction or affordances, which support choices during the design process (using design spaces, for instance). These tools rely on design recommendations resulting from the first research axis (either from theoretical frameworks directly or from behavior analysis). This axis also includes the specification of tailoring mechanisms to provide relevant features or affordances to specific users when using the technology (once the design is completed). Finally, dynamic adaptation could correspond to the system's reaction to changes in the context of use (for instance, device configuration, group dynamics, specific user behaviors, or disengagement).

The contributions are essentially technical or related to design, including the development of prototypes providing specific affordances, tailoring, or dynamic adaptation algorithms, and tools to support design choices and exploration (design space and design recommendations).

1.6. Contributions and manuscript overview

Chapter 2 describes the theoretical foundations on which my research is based. More precisely, I detail the different concepts related to UX dimensions: motivation, engagement, immersion, and related concepts, social interactions, and collaboration.

Chapter 3 presents my research on multi-surface environments and contributes mainly to my first research axis on observing and understanding users' activities and experiences with technology to inform the design, and to my third research axis on designing tailored experiences. We specified a model of collaboration and a method to describe collaborative behaviors, spatial configuration, and devices' usage (methodological contributions). Several prototypes were developed to explore how to support key elements in collaboration such as awareness and regulation, information sharing, and territoriality aspects (technical and design contributions). We conducted different studies to analyze the impact of these affordances on collaboration (empirical contributions).

ARTICLE	Journal or conference Name	UX DIMENSION					FOCUS		CONTRIBUTIONS									
		Collaboration	Engagement	Motivation	Immersion Presence	Flow	Interaction Devices config.	UI Affordances	Conceptual	Empirical	Methodological	Technical & Design	user model	Behavior analysis	Prototypes & Tools	Adaptation algo	Design space & Tools	Design Recomendations
Lachand et al. 2022	TOCHI																	
Tong et al. 2017a	CSEDU																	
Tong et al. 2017b	INTERACT																	
Tong et al. 2016 & Serna et al. 2016	MOBILE HCI & Workshop																	
Marty et al. 2016	EC-TEL																	
Lachand et al. 2016	IHM																	

Table 1.1.: Summarize of publications conducted in multi-surface environments presented in chapter 3

ARTICLE	Journal or conference Name	UX DIMENSION					FOCUS		CONTRIBUTIONS									
		Collaboration	Engagement	Motivation	Immersion Presence	Flow	Interaction Devices config.	UI Affordances	Conceptual	Empirical	Methodological	Technical & Design	user model	Behavior analysis	Prototypes & Tools	Adaptation algo	Design space & Tools	Design Recomendations
Lavoué et al. 2023	IEEE TVCG																	
Basille et al. 2023	IHM																	
Basille et al. 2022	CSEDU																	
Loup et al. 2016	EC-TEL																	
Serna et al. 2015	Workshop EIAH																	

Table 1.2.: Summarize of publications conducted in immersive learning environments an games presented in chapter 4

Chapter 4 focuses on immersive learning environments and games, and contributes to my first research axis on observing and understanding users' activities and experiences with technology to inform the design. I conducted several situated studies to investigate how technology affordances and design choices influence the experience of users and behaviors. We investigated different types of affordances (epistemic, social, immersive) on different dimensions of UX (motivation, engagement, flow, social presence) and behaviors (engaged or collaborative behaviors). The contributions of this chapter are thus mainly empirical and provide design recommendations.

Chapters 5, 6, and 7 describe my research on gamified environments, covering my three research axes: observing and understanding users' activities and experiences with technology (axis 1), modeling users (axis 2), and designing tailored experiences (axis 3). In chapter 5, we proposed a design space for meaningful gamification based on empirical findings from a study on the impact of motivational affordances (contributions related to design). In chapter 6, we identified factors specific to users that influence motivation and engagement (empirical contributions), and relying on a statistical approach, we proposed a user model integrating these factors (methodological contributions). Finally, in chapter 7, we developed an algorithm to tailor gamification combining various user profiles to recommend the most suitable game element to user characteristics (technical contribution). We then conducted a large-scale and long-term situated study to assess the impact of this tailored approach on motivation and engagement over time. The contributions of this study are both methodological and empirical.

ARTICLE	Journal or conference Name	UX DIMENSION					FOCUS		CONTRIBUTIONS									
		Collaboration	Engagement	Motivation	Immersion	Presence Flow	Interaction Devices config.	UI Affordances	Conceptual	Empirical	Methodological	Technical & Design	user model	Behavior analysis	Prototypes & Tools	Adaptation algo	Design space & Tools	Design Recomendations
Reyssier et al. 2023	Interactive Learning Env.																	
Serna et al. 2023	CHI PLAY																	
Reyssier et al. 2022	IEEE TLT																	
Lavoué et al. 2021	IJHCS																	
Lavoué & Serna. 2021	STICEF																	
Hallifax et al. 2020	AIED																	
Hallifax et al. 2019b	CHI PLAY																	
Hallifax et al. 2019a	EC-TEL																	
Hallifax et al. 2018	LBW CHI																	

Table 1.3.: Summarize of publications conducted in gamified environments presented in chapters 5, 6 and 7

Chapter 8 presents my research perspectives, moving from the three environments studied to hybrid environments. These environments offer opportunities in terms of social interactions and facilitating the completion of complex tasks, but they also raise several challenges related to discontinuities (of motivation, communication, or awareness). I propose research avenues to tackle these challenges by supporting meaningful and adapted experiences to foster motivation and sustained engagement.

2. Theoretical Foundations

Researchers and practitioners in the HCI community have widely adopted the concept of user experience, resulting in numerous definitions and dimensions that vary according to the specific technology or area of interest. In this chapter, I define the theoretical foundations of UX dimensions pertinent to my research: motivation, engagement, flow, immersion and presence, along with concepts related to social and collaborative experiences, specifically collaboration, awareness and regulation.

2.1. Self-Determination Theory and Motivation

2.1.1. Overview

Self-Determination Theory (SDT) provides a framework for understanding the factors that promote sustained motivation and healthy psychological and behavioral functioning (often called well-being) based on empirical evidence and offering practical applications across the lifespan [Deci and Ryan, 1985a; Ryan and Deci, 2000b, 2017]. SDT has become one of the most frequently used and well-validated theories employed in HCI research [Ballou et al., 2022], as well as in game research [Tyack and Mekler, 2020], virtual learning environments [Huang et al., 2019], gamification [Mekler et al., 2017; Sailer et al., 2017], behavior change [Villalobos-Zúñiga and Cherubini, 2020], and positive computing [Peters et al., 2018].

This widespread adoption is mostly due to its comprehensive framework for understanding motivation and behavior. It integrates various psychological concepts and factors, such as intrinsic and extrinsic motivation, basic psychological needs, and the role of social contexts, into a unified theory [Ryan and Deci, 2017]. SDT has been extensively researched and validated across different cultures and populations. Numerous studies have provided empirical evidence supporting the theory and its effectiveness in explaining motivation, well-being, and behavior change outcomes [Ryan and Deci, 2020]. Practical applications are another factor that contributes to SDT adoption. The theory provides insights into how to create supportive environments that foster intrinsic motivation, autonomy, competence, and relatedness, which can lead to positive outcomes [Peters et al., 2018]. It has been applied in areas such as education, healthcare, workplace motivation, sports, and more. Finally, SDT can be integrated with other theories and models, such as goal theory, cognitive evaluation theory, and social cognitive theory, among others. This flexibility allows researchers and practitioners to combine SDT with other approaches to gain a more comprehensive understanding of motivation and behavior change.

SDT consists of six mini-theories that explain different aspects of human motivation and behavior. Each mini-theory addresses a facet of motivation or personality functioning [Ryan and Deci, 2017]. Among others, the *Cognitive Evaluation Theory* (Cognitive Evaluation Theory (CET)) concerns intrinsic motivation, which is based on the satisfaction of behaving "for

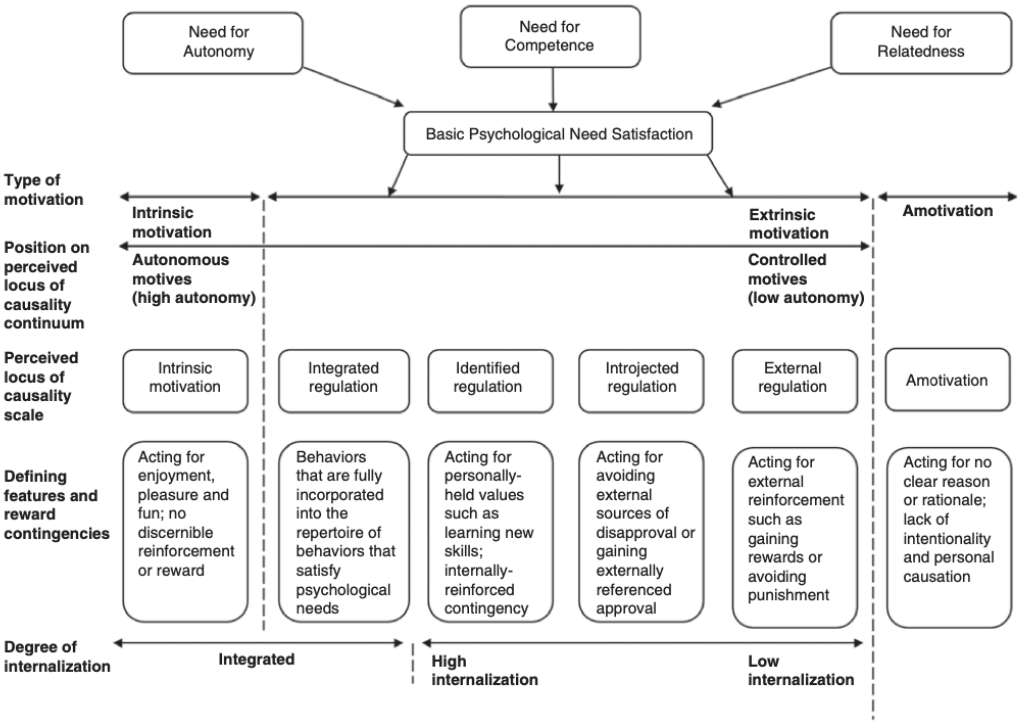


Figure 2.1.: Diagram presenting the three key mini-theories of SDT: cognitive evaluation theory (CET), organismic integration theory (OIT), and basic needs theory (BPNT), as taken from [Hagger et al., 2020].

its own sake." The CET specifically addresses the effects of social contexts on intrinsic motivation [Ryan and Deci, 2022]. The *Organismic Integration Theory* (Organismic integration theory (OIT)) explains the various types of extrinsic motivation that result from different degrees of internalization and transformation of the value and regulation of a behavior [Ryan and Deci, 2022]. The *Basic Psychological Needs Theory* (Basic psychological needs theory (BPNT)) highlights and elaborates the nature of evolved psychological needs and their relationship to psychological health and well-being [Ryan and Deci, 2022].

2.1.2. SDT Taxonomy of Motivation

According to the SDT, motivation lies on a continuum of self-determination, ranging from the most self-determined and autonomous behaviors with intrinsic motivation to the less self-determined and controlled behaviors with extrinsic motivations, and finally the absence of self-determined behaviors with amotivation (see Figure 2.1). According to the experienced and perceived locus of control, a distinction is made between autonomous types of motivation (experienced as being a result of an internal drive) and controlled types of motivation (controlled by external pressures). The different motivational states on the continuum correspond to the degree of internalization, i.e. the way individuals internalize and integrate external regulations and values into their sense of self, distinguishing: (1) intrinsic motiva-

tion, (2) integrated regulation, (3) identified regulation, (4) introjected regulation, (5) external regulation, and finally (6) amotivation.

Amotivation corresponds to the absence of motivation, where individuals lack the intention to act or have no interest in the activity.

Extrinsic motivation leads to instrumental behaviors which aim toward outcomes extrinsic to the behavior itself. In other words, this motivation deals with expected benefits from a situation, in order to receive something positive or to avoid something negative. Deci and Ryan [1985b] distinguish several forms of instrumentality, including external regulation, introjection, identification, and integration which fall along a continuum of internalization. Internalization refers to *integrating the driving regulations "with the sense of self", absorbing them and making them one's own* [Deci and Ryan, 2000]. The more internalized the extrinsic motivation, the more autonomous the person will be when enacting the behaviors. The theory underlines the importance of enhancing internalization and autonomous forms of extrinsic motivation for maintaining long-term engagement and well-being. The four extrinsic motivations correspond to the regulations on which they are based:

- *External regulation* is the most controlled form of extrinsic motivation, where a person engages in an activity to obtain a reward or avoid punishment. This motivation, which is not internalised at all, is exclusively external and regulated by compliance, conformity, and external rewards/punishments.
- *Introjected regulation* is a partially internalized form of extrinsic motivation, where contingencies are somewhat external. A person with introjected motivation engages in an activity to avoid guilt or shame, or to enhance their self-esteem.
- *Identified regulation*, which is highly internalised, is a more self-determined form of extrinsic motivation, where a person engages in an activity because they value the outcome or goal. behaviors are conducted by choice, in order to achieve specific objectives.
- *Integrated regulation* is the most integrated and self-determined form of extrinsic motivation, where a person engages in an activity because it aligns with their values, needs, personality, and sense of self.

Intrinsic motivation is the most self-determined form of motivation, where a person engages in an activity because they find it inherently interesting, enjoyable, or satisfying. Ryan and Deci [2000a] define intrinsic motivation as *the doing of an activity for its inherent satisfaction rather than for some separable consequence. When intrinsically motivated, a person is moved to act for the fun or challenge entailed rather than because of external products, pressures, or rewards.* Intrinsic motivation can be further decomposed or categorized into several subtypes or dimensions. In particular, in the educational domain, Vallerand et al. [1992]; Vallerand [1997] proposed the Hierarchical Model of Intrinsic and Extrinsic Motivation, in which they propose a decomposition of intrinsic motivation into three subtypes:

- *Intrinsic motivation to know* relates to engaging in an activity for the pleasure and satisfaction of learning, exploring, and trying to understand something new.
- *Intrinsic motivation toward accomplishment* refers to engaging in an activity for the pleasure experienced when attempting task mastery.
- *Intrinsic motivation for stimulation* is operative when one engages in an activity in order to experience pleasant sensations, excitement, or aesthetic enjoyment.

2.1.3. Basic Psychological Need Satisfaction

The theory defines three basic psychological needs, competence, autonomy, and relatedness, that are universal and essential for the psychological well-being and optimal functioning of people [Ryan and Deci, 2017]. Regulatory processes underlying goal pursuits are associated with differing degrees of need satisfaction [Deci and Ryan, 2000]. When these needs are satisfied, people are more likely to experience autonomous motivation, engagement, and flourishing. They engage in activities because they find them inherently enjoyable and satisfying. Conversely, when needs are thwarted or frustrated, individuals experience ill-being, dissatisfaction, and negative affect, among other signs of non-optimal functioning. People may become less motivated and even engage in less healthy behaviors.

- *Competence* relates to the need to feel capable, effective, and competent in one's activities and interactions with the environment. It involves seeking challenges, acquiring skills, and experiencing a sense of mastery. To support competence, it is recommended to provide individuals with opportunities for skill development, setting attainable goals and optimal challenge, and offering constructive feedback and support. Peters et al. [2018] underlines the importance of novelty and difficulty since they can provide new opportunities for learning and mastery. When satisfied, individuals capably engage in activities and experience opportunities for using and extending skills and expertise. When frustrated, they experience a sense of ineffectiveness or even failure and helplessness [Vansteenkiste et al., 2020].
- *Autonomy* refers to feeling a sense of volition and willingness. It involves a sense of personal freedom and the ability to make decisions and act in alignment with one's values and interests. Autonomy support involves providing individuals with opportunities for self-direction and encouraging independent decision-making. Autonomy can be supported when technology allows for personalization and offers options and choices in its use. From a broader perspective, technology can increase autonomy by allowing people to pursue self-determined goals, thus augmenting their capabilities [Peters et al., 2018]. When satisfied, individuals experience a greater sense of ownership, integrity, motivation in their actions. Conversely, when frustrated, individuals experience a sense of pressure and often conflict [Vansteenkiste et al., 2020].
- *Relatedness* is the need to experience a sense of belonging to a community and meaningful relationships with others. It involves feeling connected, significant, cared for, understood by others. To support relatedness, it is recommended to create inclusive and supportive social environments, fostering positive relationships, and promoting cooperation and empathy. When frustrated, individuals experience social alienation, exclusion, and loneliness [Vansteenkiste et al., 2020].

The satisfaction of these three needs depends on the way extrinsic contingencies are more or less internalised in the self [Ryan et al., 1995], determining if people are mostly intrinsically or extrinsically motivated. When they feel a sense of autonomy, competence, and relatedness in an activity, external regulations can be internalised and people are more likely to move towards more self-determined behaviors. The different SDT sub-theories highlight supports for autonomy and relatedness as critical to internalization (in OIT), and competence and autonomy in fostering intrinsic motivation (in CET).

2.1.4. Designing technology from a SDT-perspective

The SDT suggests that people can move along the continuum towards more self-determined forms of motivation, depending on the degree to which their basic psychological needs are supported. For instance, in education, need support has been recognized as beneficial for more autonomous motivation and academic performances [Ryan and Deci, 2009]. Relying on these assumptions, researchers have highlighted the importance of supporting need satisfaction in the design of technologies to offer engaging and flourishing experiences to users. Peters et al. [2018] consider basic needs as mediated variables between technology and well-being that can be used both for adjusting design and measuring the specific features of technology against these needs. To bring SDT theory into practice, the authors conceptualized a toolkit that regroups several tools for wellbeing-supportive design [1] [Peters et al., 2020; Peters and Ahmadpour, 2020; Peters et al., 2021]. In particular, they propose a deck of cards providing insights on psychological needs, heuristics, and design strategies to support wellbeing in user experience [Peters, 2023].

In game research, several systematic literature reviews identify SDT as the most frequently used theoretical framework to support the design of game elements [Seaborn and Fels, 2015b; Zainuddin et al., 2020b; Tyack and Mekler, 2020]. Researchers have started to integrate need satisfaction as design guidelines [Deterding, 2015; van Roy and Zaman, 2017] and several studies focus on assessing how game elements can support or influence basic needs [Peng et al., 2012; Mekler et al., 2017; Sailer et al., 2017; Xi and Hamari, 2019; van Roy and Zaman, 2018; Van Roy and Zaman, 2019]. Some studies found positive effects, such as Peng et al. [2012] who examined how game features impact need satisfaction and game experience. They found that autonomy-enhanced (choices) and competence-enhanced features (dynamic difficulty and mastery points) had positive effects on the corresponding need satisfaction but also on motivation and engagement outcomes. Sailer et al. [2017] showed that specific game design elements have specific psychological effects (for instance badges and leaderboards enhancing competence, and avatars and teammates promoting social relatedness). Xi and Hamari [2019] explored the relationship between gamification features and intrinsic need satisfaction, revealing that achievement and social gamification predicted satisfaction of all three needs, and immersion gamification only predicted autonomy need satisfaction. However, studies found more mixed results. Mekler et al. [2017] did not observe such an effect of gamification on intrinsic motivation and competence need satisfaction. They suggest that in their specific context, game elements acted as extrinsic incentives. Similarly, Van Roy and Zaman [2019] highlight the ambivalent motivational power of gamification, observing both positive and negative effects. They underlined the importance of considering situational factors, which play a role in shaping feelings of autonomy, competence, and relatedness.

Despite the wide use of SDT in the design of technology, Tyack and Mekler [2020] highlight conceptual gaps at the intersection of SDT and HCI games research. They point out that SDT concepts and mini-theories are often not explicitly considered in research papers, leading to potential theoretical inconsistencies and misconceptions. They argue that *more in-depth engagement with the theoretical underpinnings of SDT-based concepts and measures would facilitate incremental knowledge gains, comparison between works, and integrating seemingly disparate research strands.*

[1] https://www.positivecomputing.org/blog/wellbeing-supportive-design-toolkit

2.1.5. Measure

Motivation is mostly measured subjectively, using declarative data and questionnaires. SDT offers a wide range of validated instruments to assess different constructs contained within the theory, in particular the satisfaction of needs and the different types of motivation.

Regarding need satisfaction, the Basic Psychological Need Satisfaction Scale (BPNSS) assesses the degree to which people feel satisfaction of the three basic needs in general and for domain specific forms for work and relationships [Chen et al., 2015]. In the domain of video games, Ryan et al. [2006] developed the PENS (Player Experience of Need Satisfaction) to measure need satisfaction in play and game players' experience. The scale has been validated [Johnson et al., 2018] and used in various studies, for instance in immersive environments [Ijaz et al., 2020]. In addition to the assessment of the three needs (Competence, Autonomy, Relatedness), they include a measure of Presence/Immersion and Intuitive Controls. They believe that intrinsic motivation in gaming contexts is associated with presence (in opposition to a person that would feel external to the game world). Peters et al. [2018] propose an adaptation of the PENS for non-game technology with two questionnaires: the TENS-Interface questionnaire (Technology-based Experience of Need Satisfaction–Interface) and the TENS-Task questionnaire (Technology-based Experience of Need Satisfaction-Task) assessing the three basic needs regarding the use of a particular technology.

Regarding motivation, several scales measure different aspects of motivation. For instance, the IMI (Intrinsic Motivation Inventory) [Ryan et al., 1983] is a multidimensional scale that assesses participants' subjective experience related to a target activity in laboratory experiments regarding intrinsic motivation and self-regulation. The instrument is composed of six sub-scales: interest/enjoyment (considered the self-report measure of intrinsic motivation), perceived competence and perceived choice (positive predictors of intrinsic motivation), felt pressure and tension (negative predictor of intrinsic motivation), effort and value/usefulness (used for internalization and self-regulation). The instrument presents some limitations since it does not assess other types of motivation besides intrinsic motivation and it focuses more on determinants and consequences of intrinsic motivation rather than motivation per se. To tackle these limitations, Guay et al. [2001] proposed another scale to measure the different types of motivation, including intrinsic and extrinsic motivation and amotivation, during an activity. They define situational motivation as *the motivation individuals experience when they are currently engaging in an activity.* Finally, in the specific domain of education, the Academic Motivation Scale (AMS) questionnaire measures the different types of motivation regarding learning [Vallerand et al., 1992]. The scale allows a very precise measure of intrinsic motivation since it distinguishes three types of intrinsic motivations (detailed in section 2.1.2) along with the extrinsic motivations and amotivation.

2.2. Engagement

2.2.1. Definition

Engagement is a complex and multidimensional construct which has been studied in various domains sometimes considered as an outcome, other times as a process. Here, I present the definitions related to UX in general, game research, and education.

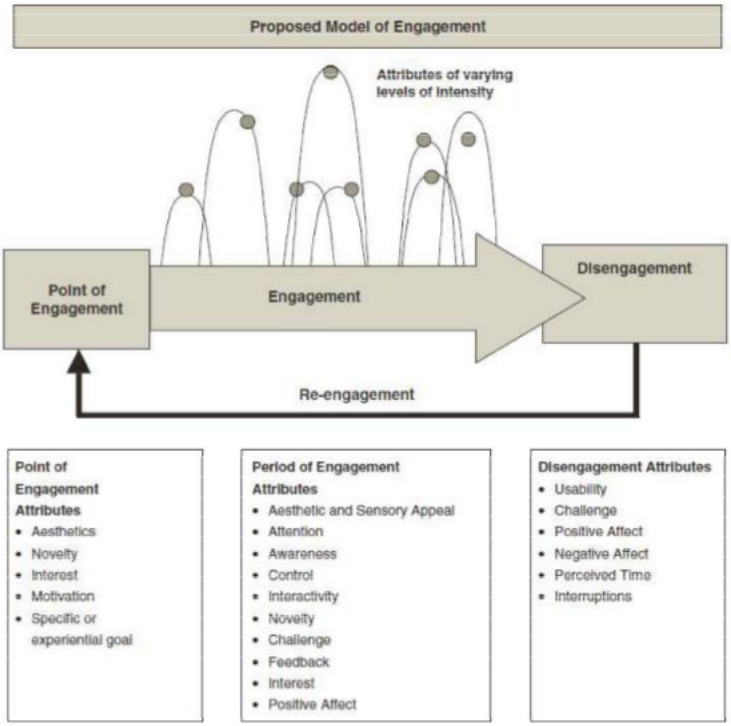


Figure 2.2.: Model of engagement and its attributes proposed by [O'Brien and Toms, 2008].

As presented in the introduction, the concept of UX has progressively evolved to focus on designing engaging experiences [Hassenzahl and Tractinsky, 2006; Peters et al., 2018]. An increasing number of works integrate the concepts of motivation and engagement in their studies. While aspects related to motivation are well-defined, with a majority relying on the SDT, the conceptualization of engagement is much more ambiguous, with different definitions, different levels of abstraction (conceptual or operational definitions), and involving various underlying concepts according to the application domain or the lens of observation.

From the UX perspective, which is the most general point of view, O'Brien and Toms [2008] conceptually and operationally define engagement. Drawing on several theories, notably flow [Czikszentmihalyi, 1990], they define engagement as *"a quality of user experience characterised by attributes of challenge, positive affect, endurability, aesthetic and sensory appeal, attention, feedback, variety/novelty, interactivity, and perceived user control."* They emphasize that engagement is a dynamic and cyclical process, with engagement and disengagement points, creating a range of engaging experiences that vary in intensity, as illustrated in Figure 2.2.

Game research also heavily studies the concept of engagement, often related to immersion. For instance, Brown and Cairns [2004] define immersion as the degree of involvement with a game, each level conditioned by removable barriers. Engagement is the first level of involvement, where the gamer must invest time, effort (accessible game controls and expected rewards), and attention (concentration). Engrossment is the second level and is related to the game design. Finally, the last level corresponds to total immersion, where the gamer has a strong feeling of presence and disconnected from reality. The authors highlight the

importance of attention and argue the level of immersion experienced is correlated to the number of attentional sources needed (visual, auditory, and mental). The authors conclude that immersion has strong parallels with flow (attention needed, sense of time altered, and loss of sense of self).

These two definitions delineate engagement as a mental state, quite close to the concept of flow, with some attributes that can be considered more at a technical level. Some elements refer to technological features (user control, attentional stimuli) or game/technology design (aesthetics, relevance, or novelty of tasks or features).

In their definition of engagement, Bouvier et al. [2014a] make a clear distinction between concepts that depend on technological aspects and media factors, such as immersion and involvement, and those related to engagement and presence, based on shifts in players' attention and consciousness from the real world to the digital environment, as illustrated in Figure 2.3. They define *engagement as the willingness to have emotions, affect and thoughts directed towards and aroused by the mediated activity in order to achieve a specific objective.* For the authors, engagement corresponds to the shift of attention towards the content of the activity, whereas consciousness is still directed towards the real world, "*since engagement does not require a loss of mental contact with the real world.*" In contrast, presence and flow involve shifting consciousness inside the game.

To structure the analysis of engagement, they identified four types of engaged behaviors, particularly in games, based on SDT:

- *Environment-directed behaviors*, related to the need for autonomy, including contemplation, curiosity, and exploration, depending on the ability to explore and modify the environment.
- *Social-directed behaviors*, related to the need for relatedness, involving opportunities to create, expand, or engage in social relationships with other players.
- *Self-directed behaviors*, related to the need for autonomy, focusing on the connections between a player and their character through identification and ownership aspects.
- *Action-directed behaviors*, related to the needs for competence and autonomy, involving actions performed in the game, including mastering the game, completing challenges, and developing strategies.

Finally, engagement has been extensively studied in educational settings. In educational research, the concept is significantly different from that defined for games or user experience in general, and focuses on its relationship with learning, emphasizing academic tasks and activities. Although there is a lack of consensus on the definition of engagement construct, there is minimal agreement that engagement is multidimensional, with at least behavioral and affective components [Reschly and Christenson, 2012]. Generally, researchers adopt a three-type model of engagement composed of *cognitive*, *motivational/affective*, and *behavioral* dimensions [Linnenbrink and Pintrich, 2003; Fredricks et al., 2004]. In addition, some authors distinguish two sub-types of behavioral engagement: academic and behavioral [Appleton et al., 2008; Reschly and Christenson, 2012].

- *Behavioral engagement* includes positive conduct (e.g., following rules), involvement in learning and academic tasks (e.g., effort, persistence, asking questions, contributing to class discussion), and participation in school-related activities [Fredricks et al., 2004]. This typically refers to the observable actions of the learner in completing a learning task [Linnenbrink and Pintrich, 2003].

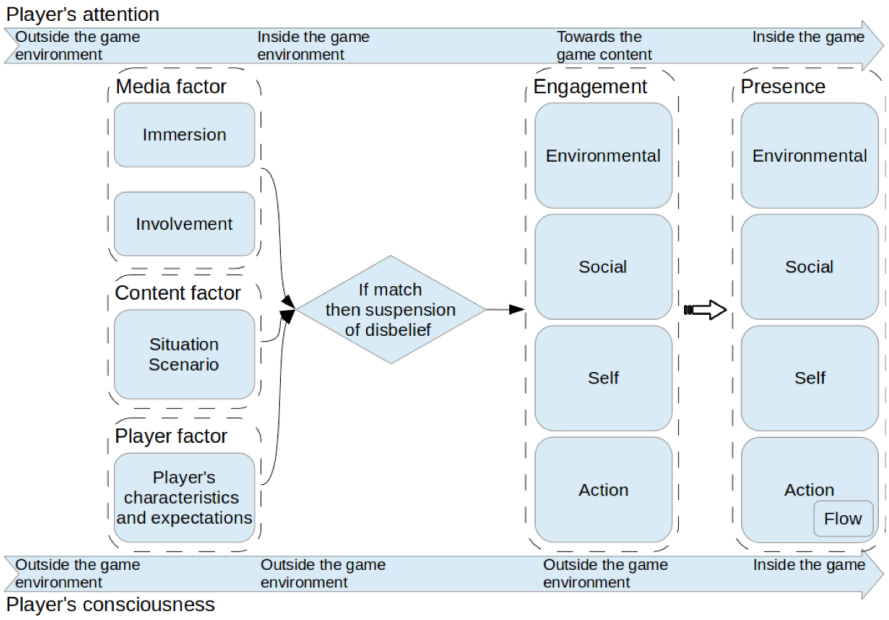


Figure 2.3.: Model of engagement proposed by [Bouvier et al., 2014a].

- *Cognitive engagement* is related to the deployment of learning strategies: cognitive, self-regulated, or resource management-related [Pintrich, 2004; Fredricks et al., 2004]. Linnenbrink and Pintrich [2003] underline that students are more cognitively engaged when they are metacognitive, meaning that *they reflect on their own thinking, actions, and behavior and monitor and regulate their own learning.* For some authors, cognitive engagement is stronger than behavioral engagement in that students can be behaviorally engaged but not cognitively engaged [Linnenbrink and Pintrich, 2003].
- *Affective/Motivational engagement* covers intrinsic interest (i.e., interest in the content or task), emotions (emotional experiences and reactions), and values (value beliefs about the general importance of the content or task considering their general goals in life) perceived by learners during learning activities [Linnenbrink and Pintrich, 2003; Fredricks et al., 2004].

Reschly and Christenson [2012] conceptualize engagement as *a mediator between the contextual influences (facilitators) and our learning outcomes across academic, social, and emotional domains*, represented in Figure 2.4. In their model, the context is broader than just the technology used and includes family, peers, school, and community aspects. They consider engagement as an outcome but also as a process. According to the authors, cognitive and affective engagement, which represent student perceptions, may have an impact on student behaviors, thus becoming mediators of academic and behavioral engagement. In this case, engagement corresponds both to processes and mental states, and observable behaviors.

2.2.2. Difference between Engagement and Motivation

Engagement and motivation are interconnected concepts, each influencing the other. According to Reeve [2012], researchers *who study motivation consider engagement mostly as an*

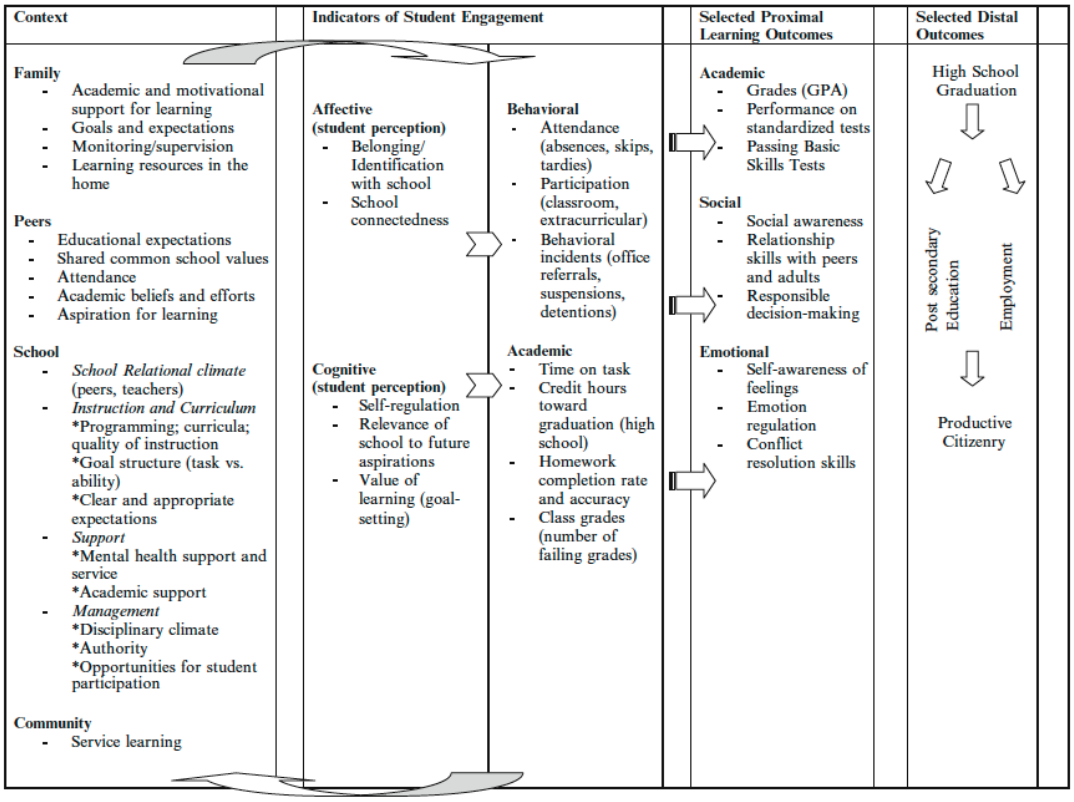


Figure 2.4.: Model of associations between context, engagement, and student outcomes proposed by [Reschly and Christenson, 2012].

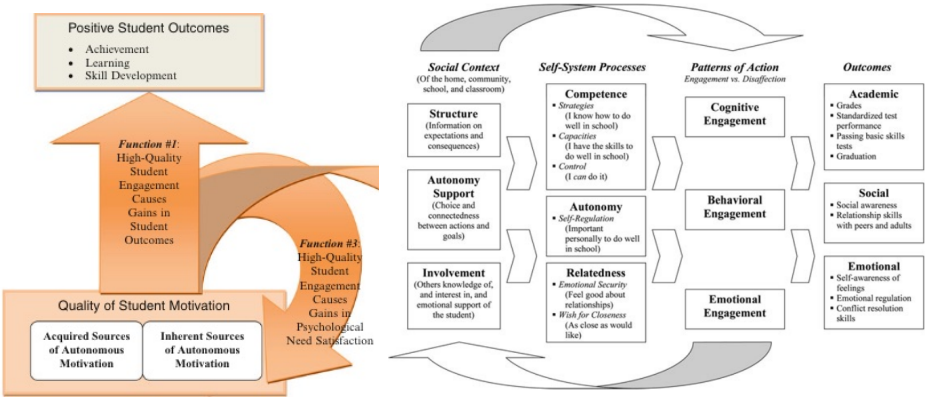


Figure 2.5.: Left side: Engagement and its relationship with motivation proposed by [Reeve, 2012]. Right side: model of engagement and self-processes model applied to Education proposed by Appleton et al. [2008].

outcome of motivational processes, whereas those who study engagement are interested mostly in motivation as a source of engagement.

From the SDT perspective, Vallerand [1997] indicate that behavioral, cognitive, and affective outcomes can be explained by the different types of motivational regulation. Pintrich [1999] argue that motivation can help promote self-regulated learning by increasing the level of engagement necessary to use self-regulatory strategies. In addition, various studies have shown that motivation positively influences engagement, such as participation in classroom tasks [Ryan and Deci, 2017] or engagement in prosocial behavior [Gagné, 2003].

From the engagement literature, motivation is usually seen as an intent and engagement as action. Reschly and Christenson [2012] underline that *engagement is defined by an observable, action-oriented subtype (behavioral) and two internal ones (cognitive and affective engagement) but then is differentiated from motivation as engagement being action (observable behavior), motivation as intent (internal)*. For Reeve [2012], motivation is a private and unobservable psychological process that serves as an antecedent cause to engagement, which is a publicly observable behavior. Most of these researchers agree that motivation has an influence on engagement. Skinner et al. [2009], for instance, demonstrated that autonomous motivation leads to behavioral and emotional engagement. Some authors go one step further. Reeve [2012] argues that engagement mediates the effects of motivation on positive student outcomes. More importantly, for Reeve, engagement can also change motivation if there are changes in students' psychological need satisfaction (see left side of Figure 2.5). Similarly, Appleton et al. [2008] propose a model of engagement based on the self-processes model of Connell and Wellborn [1991] based on the three fundamental psychological needs defined in SDT (Right side of Figure 2.5). Because engagement can change via cyclic interactions with contextual variables, the authors argue that it should be studied within a motivational framework. In this approach, researchers consider individual needs to mediate contextual factors and engagement [Fredricks et al., 2004]. This resonates with the Motivation, Engagement, and Thriving in User Experience (METUX) model [Peters et al., 2018] where the basic psychological needs mediate positive user experience, especially motivation and engagement. Finally, this cyclical vision of engagement is in line with the model of O'Brien and Toms [2008], which specifies motivation as one of the points of engagement (and re-engagement) attributes.

2.2.3. Measure

Many studies focus on analyzing engagement, resulting in a wide variety of measures, often linked to the theoretical frameworks upon which they are based. It is in the field of education that the most advanced measures are found, corresponding to the multi-dimensional definition of engagement. These coexisting approaches have generated a large variety of indicators to measure the level of engagement of users.

Self-report measures and qualitative methods

A first approach to measure engagement consists of collecting data on users' experience, either through qualitative methods (observation, ethnography) or through standardized or ad-hoc questionnaires after the use of a system. The main objective of self-report measures is to provide efficient means of assessing users' perception of their level of engagement and understand both cognitive and emotional dimensions of engagement.

For instance, da Rocha Seixas et al. [2016] defined engagement indicators (such as autonomy or participation) with ethnographic methods, using observation and semi-structured interviews. Using an ad-hoc survey completed by students at the end of the experiment, they also performed a cluster analysis to classify student engagement.

Regarding standardized surveys, O'Brien and Toms [2010] developed the User Engagement Scale (UES), a multidimensional scale to measure user engagement, grounded in their attributes-based model of engagement [O'Brien and Toms, 2008] presented in section 2.2.1. The scale is composed of 31 items distributed across six dimensions:

- Focused attention: focused attention, awareness, and perceptions of time (similar to characteristics of Flow).
- Perceived usability: negative affect experienced as a result of the interaction and the degree of control and effort expended.
- Aesthetics: the attractiveness and visual appeal of the interface.
- Endurability: the overall success of the interaction and users' willingness to recommend an application to others or engage with it in the future.
- Novelty: curiosity and interest in the interactive task.
- Felt involvement: the sense of being drawn in and having fun.

The scale has been widely used, and several studies have provided empirical evidence to suggest a four-factor model instead of six. O'Brien et al. [2018] then proposed a short form of the scale with the following four dimensions: Focused Attention, Perceived Usability, Aesthetic Appeal, and Reward.

Objective measures

Objective measures, consisting mostly of physiological metrics and performance indicators, provide the advantage of being collected during the entire period of system use, suitable for behavioral engagement analysis. Some approaches rely on intrusive techniques to collect physiological measures (e.g., heart rate, blood pressure, EEG) [Fairclough et al., 2013], emotional states [Mandryk et al., 2006], or behavioral measures such as gaze tracking [Jennett et al., 2008]. These approaches are usually expensive, time-consuming, and dependent on signal strength [Kivikangas et al., 2011]. Furthermore, determining which signal or manifestations are really inherent to user engagement can be very complex [Bouvier et al., 2014b]. Finally, other methods rely on collecting and analyzing data gathered from the interaction with the system to extract useful information about users' engagement in a non-intrusive or disruptive way. Two approaches can be distinguished according to how data is interpreted: theory-driven approaches and learning analytics and statistical approaches.

Theory-driven approach

Bouvier et al. [2014b] propose an hybrid approach combining a theory-driven and a qualitative approach to identify users' engagement and qualify their engaged behaviors from data logs. The authors rely on three theoretical frameworks: the Self-Determination Theory, the Activity Theory, and the Trace Theory combined through a three-stage process. Users' engaged behaviors are qualified according to four categories: environmental-directed, social-directed, self-directed, and action-directed defined in [Bouvier et al., 2014a]. In their model, these high-level engaged behaviors are decomposed into activities. Then, an activity corresponds to a chain of actions (i.e., an aggregation of actions) performed by the user. An action is decomposed into a chain of operations, corresponding to the collected data (i.e., interaction performed through input devices). Analyzing chains of actions rather than single actions provides comprehensive contextual information on behaviors, facilitating their understanding.

Learning analytics and statistical approaches

In the field of Education, most studies adopt learning analytics [Lang et al., 2017; Heilbrunn et al., 2017]. These approaches rely on student activity (i.e., actions in the learning environment) to measure behavioral engagement by directly extracting indicators from data logs. Generally, these indicators correspond to the time spent in the learning environment, number of logins, content completion rate, completed test rate, number of questions answered correctly, etc. [Taşkın and Kılıç Çakmak, 2022]. For instance, Ding et al. [2018] measured student behavioral engagement through students' number of entries and frequency of logins. Rodrigues et al. [2022a] used the number of attempts students made, the time spent on the environment, and the number of system accesses to measure students' intentions to practice, consult learning materials, and interact with game elements. Usually, these studies present a cumulative view of the indicators, without temporal analysis sessions after sessions. Recently, some longitudinal studies have started to examine this temporal aspect, such as Barata et al. [2017], who used performance and participation measures to identify clusters of students and analyze their evolution over three years. Taşkın and Kılıç Çakmak [2022] examined the role of gamification on the behavioral engagement of students, using

the number of logins, time spent in the environment, and content review rate over ten weeks and observed the distribution of the indicators over time.

Finally, some studies have begun to investigate correlations between these indicators, defining behavioral patterns or engagement models. For instance, Codish and Ravid [2015] defined gamification behavior patterns as sequences of actions performed by a user that can be extracted from the data logs. Another interesting method is presented in Fincham et al. [2019], where the authors used a factor analysis to establish an engagement model based on various simple indicators. The indicators are inspired by the review performed by Joksimović et al. [2018] and are derived from data logs, referring to behavioral or academic engagement (e.g., days active, question accuracy). From all these metrics, the authors built a final engagement model based on three factors of engagement.

2.3. Immersion and related concepts

Many studies have investigated how users feel and behave in virtual environments through the tightly related concepts of immersion and presence [Sanchez-Vives and Slater, 2005] often also referring to the theory of flow [Suh and Prophet, 2018].

2.3.1. Flow

Definition

Flow, defined as a state of profound enjoyment and concentration experienced during activities, is a key concept in theories of positive experience. Czikszentmihalyi [1990] studied flow to understand the phenomenon of intrinsically motivated and autotelic activity (i.e., an activity that is rewarding in itself without extrinsic rewards, such as reading, for instance). Flow is described as *the experience of complete absorption in the present moment* [Nakamura and Csikszentmihalyi, 2009], and is usually associated with deep immersion, focus, and intrinsic motivation in the activity. The concept is widely adopted in various contexts, such as games, education, sports, and the workplace.

Flow is defined as the optimal experience, arising when (1) perceived challenges of the activity are in line with the user's capabilities ; and (2) the activity goals are explicit and reachable, and users receive instant feedback on their progress [Czikszentmihalyi, 1990; Nakamura and Csikszentmihalyi, 2009]. Most works and measurement instruments investigating the flow state and the conditions for experiencing it are based on the nine interconnected dimensions defined by Czikszentmihalyi [1990]. Three of these dimensions correspond to the conditions (or antecedents) for entering flow [Nakamura and Csikszentmihalyi, 2009] :

- Challenge-skill balance : perceived opportunities for action (challenges) are in balance with perceived action capabilities (skills). Users must be confident in their ability to complete the activity. Entering into flow depends on finding the optimal balance. If challenges exceed skills, individuals may experience anxiety , while unchallenging activities may provoke boredom [Nakamura and Csikszentmihalyi, 2009].

- Clear goals : this dimension corresponds to a strong sense of what needs to be achieved in the activity, allowing individuals' attention to be undivided. Goals are clearly ordered and sequenced . They can be set either in advance or developed out of engagement in the activity [Jackson and Marsh, 1996].
- Immediate and unambiguous feedback : this dimension corresponds to the information received when succeeding at a goal [Jackson and Marsh, 1996]. This helps to maintain or adjust behavior in line with activity goals to maintain the flow state [Hassan et al., 2020].

The other six dimensions describe the characteristics of flow itself:

- Intense and focused concentration : this aspect describes total focus in the present on a specific task. This dimension is one of the most important in the experience of flow [Czikszentmihalyi, 1990].
- Merging of actions and awareness : during flow, actions are completed almost "automatically," with no awareness of the self as separate from the actions being performed [Jackson and Marsh, 1996].
- Loss of reflective self-consciousness : Jackson and Marsh [1996] explain that this dimension involves the disappearance of concern for the self during flow. They specify that "*the absence of preoccupation with self does not mean the person is unaware of what is happening in their mind and body, but rather is not focusing on the information normally used to represent to oneself who one is*".
- Sense of actions control : this dimension encompasses a sense of exercising control, without the person actively trying to exert control [Jackson and Marsh, 1996]. It also corresponds to feeling confident in handling the task at hand , which sometimes is associated with flow preconditions [Hassan et al., 2020].
- Distortion of temporal experience : this dimension corresponds to a change in time perception, either slowing down or speeding up. Alternatively, time may simply become irrelevant and beyond individuals' awareness [Jackson and Marsh, 1996]. However, Czikszentmihalyi [1990] noted that this dimension may not be universal since some activities require time awareness to be completed successfully (in particular in sports).
- Autotelic experience : an intrinsic feeling of rewarding activity, worth doing for its own sake. This dimension provides high motivation towards further engagement [Jackson and Marsh, 1996] and is considered the end result of being in flow Czikszentmihalyi [1990].

To experience flow, the activity must provide all the preconditions for flow, so that the individual feels the other six dimensions of flow at the same time [Oliveira et al., 2023b]. In their recent study, Hassan et al. [2020] investigate the preconditions of experiencing flow in VR. They proposed a heuristic model of associations between the preconditions of flow (including sense of control) and the dimensions of flow itself. Based on this model, they demonstrated that experiences of flow in VR are associated with intentions to continue VR use and with longer VR sessions. Different studies have highlighted flow as a key component of user experience in achieving desired behaviors [Oliveira et al., 2023b]. Additionally, in the field of education, flow is frequently associated with increased student engagement and enjoyment [Shernoff et al., 2003], and research explores its impact on learning outcomes [Csikszentmihalyi, 2014].

One challenge in these studies is to understand how to design technologies to induce flow [Hassan et al., 2020]. For instance, in game research, Sweetser and Wyeth [2005] developed the GameFlow model, a model of player enjoyment, structured into eight elements that can be mapped to the concept of flow. The authors define a set of criteria and heuristics for informing the design of each element and evaluating flow in all types of video games. However, the authors also recognize the complexity of operationalizing due to the generic nature of the model and aim to define more specific, low-level, and implementable criteria for a specific game type [Sweetser et al., 2012].

Measure

Flow is usually considered part of the user experience and is measured through self-reported measures using standardized flow scales. Various versions of these scales, both short and long, rely on the nine dimensions of flow defined by Czikszentmihalyi [1990], as proposed by Jackson and colleagues [Jackson and Marsh, 1996; Jackson and Eklund, 2002; Jackson et al., 2008]. The Flow State Scale (FSS) [Jackson and Marsh, 1996] considers the flow experience in a given situation, while the Dispositional Flow Scale (DFS) [Jackson and Eklund, 2002] assesses the tendency to experience flow. Some studies have demonstrated the reliability of the Dispositional Flow Scale-2 (DFS-2) in the context of gamification [Hamari and Koivisto, 2014] and in VR settings [Hassan et al., 2020].

However, some studies highlight the limitations of this type of measurement and argue for a more objective approach to identify flow experience automatically. Some works propose non-invasive approaches, as opposed to physiological measures, relying on data logs to identify flow experience using learning analytics, data mining, or machine learning techniques [Lee et al., 2014; Semerci and Goularas, 2020; Oliveira et al., 2023b,a]. For instance, Semerci and Goularas [2020] extracted student behavioral patterns based on mouse interactions using deep learning methods and showed a significant correlation between these patterns and the flow experienced. Oliveira et al. [2023b] proposed association rules, using data mining, between users' behavior data (e.g., mouse clicks, activity time in the system, and average response time) and their self-reported flow experience.

2.3.2. Immersion

Immersion is a dimension of user experience that is widely studied in VR literature [Szabo and Gilanyi, 2020; Agrawal et al., 2020] and game research [Brown and Cairns, 2004; Jennett et al., 2008]. According to various studies, the boundaries between different concepts such as immersion, engagement, or presence are not always well defined. Sometimes the terms immersion and presence are even used interchangeably. Thus some authors have attempted to formalize the concept more clearly. From the original description of Murray [1997], where *immersion is a metaphorical term derived from the physical experience of being submerged in water*, there is a consensus on the fact that immersion involves being or feeling surrounded by something [Nilsson et al., 2016]. From this, two main approaches emerge in defining the concept [Szabo and Gilanyi, 2020]. In their literature review, Agrawal et al. [2020] summarize these trends in a diagram represented in Figure 2.6.

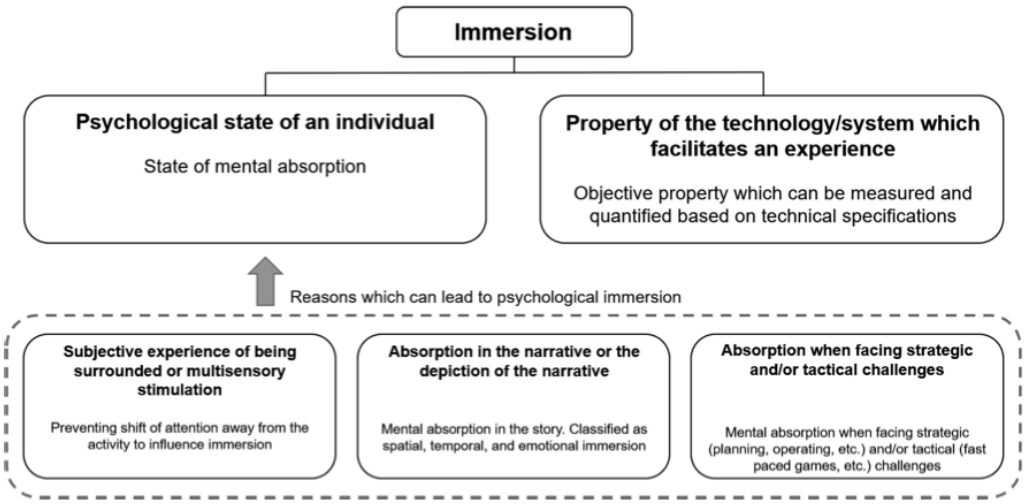


Figure 2.6.: Diagram summarizing [Agrawal et al., 2020] literature review on immersion. The different types of immersion that can lead to psychological immersion are taken from Nilsson et al. [2016].

Immersion as a psychological state

The first trend, which is the most developed, considers immersion as an individual's psychological state. For Witmer and Singer [1998], immersion corresponds to *a feeling of being enveloped by, included in, and interacting with the virtual environment that provides a continuous stream of stimuli and experiences*. For them, natural interaction is important to support immersion in the virtual environment. They also distinguish immersion from involvement, stating that the latter is a psychological state that results from assigning great focus and attention to perceived stimuli and occurring events. Many studies in VR research adopt this vision, proposing slightly different definitions (listed in literature reviews such as [Agrawal et al., 2020; Szabo and Gilanyi, 2020]).

However, the distinction between the concepts is quite confusing in other definitions. As already introduced in the engagement section, Brown and Cairns [2004] describe immersion as the degree of involvement with a game, divided into three levels: engagement, engrossment, and total immersion. Their definition shares several elements with the definition of flow (alteration of the sense of time or awareness of the real world). Based on this definition, Jennett et al. [2008] state that immersion is the psychological experience of engaging with a computer game. They make a distinction from flow since 1) it does not necessarily need to be the most optimal experience; and 2) immersion can also generate negative emotions (in contrast to flow generating only positive experiences).

Finally, after their literature review on immersion, Agrawal et al. [2020] argue that sensory stimulation is not required to experience immersion, and they propose the following definition: *Immersion is a phenomenon experienced by an individual when they are in a state of deep mental involvement in which their cognitive processes (with or without sensory stimulation) cause a shift in their attentional state such that one may experience disassociation from the awareness of the physical world.* Relying on the categorization of Nilsson et al. [2016], they identify three main reasons leading to this psychological immersion. Immersion as the experience of technolog-

ical envelopment (or surrounding) corresponds to the subjective experience related to the media form. Nilsson et al. [2016] explain that *form factors, such as isolation from the physical environment and interfaces allowing for natural interaction, are believed to influence the experience of immersion*. Narrative immersion, divided into temporal, spatial, and emotional immersion, is characterized by the degree of mental absorption with the story of an immersive experience. It is thus related to the mediated content, rather than the form of the technology. Finally, in the field of video games, immersion can be considered as a response to challenges. It is reached due to a balance between challenges and abilities, which comes very close to the definition of flow. However, Agrawal et al. [2020] argue that immersion and flow should be considered as two distinct concepts since *flow is an "all-or-nothing" extreme experience, which limits it to optimal, positive experience, while immersion is a graded experience*.

This lack of clear distinction between concepts makes the measurement of immersion quite challenging. Questionnaires quantifying immersion are often developed for measuring presence, engagement, or the gaming experience. In these questionnaires, immersion is assessed as a factor. They are often context-dependent, involving many items with overlapping concepts.

Immersion as a system property

The second trend defines immersion as an objective property of a technology. In opposition to Witmer and Singer, Slater rejects the fact that immersion is a subjective experience, reserving this distinction for the concept of presence [Slater, 1999, 2003]. He argues that the term immersion should be reserved for the characteristics that a system objectively delivers in terms of perceptual stimuli in the same way as Biocca and Levy [1995]. For him, *the more that a system delivers displays (in all sensory modalities) and tracking that preserves fidelity in relation to their equivalent real-world sensory modalities, the more that it is "immersive"*. Some authors embrace this vision, using terms such as technological immersion, perceptual immersion or sensory immersion (in opposition to the psychological immersion defined in the first trend) [Szabo and Gilanyi, 2020]. Skarbez et al. [2017] adopt Slater's vision, pointing out that *Slater's immersion is what makes it possible to experience Witmer and Singer's immersion*. Finally, closely related to this, authors adopting the psychological approach to immersion introduce the concept of "immersive potential" to designate the potential of a system or content to elicit immersion [Agrawal et al., 2020].

In this approach, immersion can be measured objectively by the technological affordances of the system. In their meta-analysis, Cummings and Bailenson [2016] identified a list of immersive features such as the tracking level, stereoscopic vision, image quality, user perspective, field of view, sound quality, etc. Their results show that technological immersion has a medium-sized effect on the presence experienced. This technological immersion can therefore be considered a factor in psychological immersion as measured by the sense of presence.

2.3.3. Presence

Presence is defined as the sense of "*being there*" by Slater [1999] and Sanchez-Vives and Slater [2005], and as the *subjective experience of being in one place or environment, even when one is physically situated in another* by Witmer and Singer [1998]. The concept is grounded in the ability to perform actions in the virtual environment and the affordances it offers.

For instance, Bystrom et al. [1999] proposed the Immersion, Presence, Performance (IPP) model to explain the relationships between immersion, presence , task performance based on Slater and colleagues' definition. In this model, the features of display technologies influence immersion (i.e. quantifiable features associated with an input device or position sensor), which in turn contributes to the fidelity of the sensory information displayed to users, thereby fostering a sense of presence in the virtual environment. The authors argue that experiencing a sense of presence is essential for performance, and that the nature of the task and user actions can also indirectly affect the level of presence, creating a feedback loop inspired by flow theory.

On the basis of this general definition, research breaking down presence into more precise concepts varies. For instance, Slater [2009] and, most recently, Slater et al. [2022] suggest dividing presence into two dimensions: place illusion and plausibility. Place illusion corresponds to *the strong illusion of being in a place in spite of the sure knowledge that you are not there*. Plausibility is the illusion that the events in the virtual environment are actually happening despite the knowledge that the events are digitally generated. In their literature review on presence, Skarbez et al. [2017] define presence as the perceived realness of a mediated or virtual experience, and they propose a model in which presence is a function of Place Illusion, Plausibility Illusion, and Social Presence Illusion. They claim that presence arises from the immersion of the technology, the coherence of the scenario, and the company offered in the virtual experience.

Other researchers avoid the term "illusion" due to its negative connotation, such as Lee [2004], who divides presence into three different sub-concepts: physical, self-presence, and social presence. Each sub-concept corresponds to a psychological state in which virtual physical objects, social actors, or self/selves are experienced as actual physical objects, social actors, or self/selves. Regarding physical presence , which corresponds to place illusion, the author argues that *no sense of transportation is required for physical presence to occur, and this approach makes it possible to encompass virtual experiences created by low-tech media*.

Relying on these various definitions, different studies explore the effects of presence on various outcomes, such as learning [Schrader, 2013; Bachen et al., 2016; Richardson et al., 2017] or participation in collaboration [Zhao et al., 2014] and communication [Oh et al., 2018] for social presence.

Social presence

Social presence can be defined as the feeling of "being with others" [Heeter, 1992]. The concept was first introduced to understand communication and interactions that took place on different forms of media. The concept was then extended to all systems designed to improve human communication for collaborative work [Biocca and Harms, 2002]. Various definitions were proposed, but the definition of Biocca and Harms [2002] is the most adopted, as noted by [Skarbez et al., 2017]. The authors define social presence as *the moment-to-moment awareness of co-presence of a mediated body and the sense of accessibility of the other being's psychological, emotional, and intentional states* [Biocca and Harms, 2002].

They consider that the sense of social presence varies over the interactions according to different levels and dimensions. The first level, the perceptual level, corresponds to a sense of spatial co-presence of the other's mediated body. They rely on Goffman [1963] , who defined co-presence as mutual awareness, with individuals being able to perceive others and others being able to perceive them. At this level, there are only minimal and automatic attributions

about the internal states of the other. The second level, called the subjective level, refers to the psychobehavioral accessibility of the other. It corresponds to the user's sense of awareness and access to the other's attentional engagement, emotional state, comprehension, and behavioral interaction. Finally, the third level, called the intersubjective level, corresponds to mutual social presence and perceived symmetry. *The user's sense of social presence is in part a function of how they perceive the other's sense of social presence of them* [Biocca and Harms, 2002].

Measure

In their literature review on measuring presence, Grassini and Laumann [2020] identify four methods to measure presence : questionnaires, interviews, physiological measures , analysis of users' behavior. Since presence is a subjective experience, the most frequently used method is based on questionnaires, which are universal and can be applied to any scenario as noted by Slater et al. [2022]. Various questionnaires have been proposed in the literature such as Slater Usoh Steed Presence Questionnaire (SUS) [Slater et al., 1994], Presence Questionnaire (PQ) [Witmer and Singer, 1998], Igroup Presence Questionnaire (IPQ) (IPQ) [Schubert et al., 2001], Temple Presence Inventory (TPI) [Lombard et al., 2009] , Networked Minds Social Presence Inventory (SPI) [Biocca et al., 2003]. However, the use of questionnaires presents some limitations, mainly due to the number of questionnaires, the variety of constructs explored, and the overall lack of a standard definition for presence [Grassini and Laumann, 2020]. In addition, Slater et al. [2022] highlight potential bias when collecting participants' perceptions by "forcing" them to think about this concept. To obtain more objective measures, physiological and behavioral methods explore how indicators such as brain activity or heart rate can predict or be correlated to the sense of presence. For instance, Ochs et al. [2022] propose a machine learning approach to predict the sense of social presence using behavioral multimodal measures related to speech (length of sentences for example). Even if these approaches seem promising, they are specific to the environment or the activity , and there is a lack of a standard for the analysis of physiological data [Grassini and Laumann, 2020]. Thus, this approach is difficult to generalize [Slater et al., 2022].

2.4. Social and collaborative user experience

2.4.1. Social interaction

In cognitive science, social interaction can be defined as follows: *Two or more autonomous agents co-regulating their coupling with the effect that their autonomy is not destroyed and their relational dynamics acquire an autonomy of their own* [Jaegher et al., 2010]. Examples of social interaction according to this definition are conversations, collaborative work, arguments or collective action.

Social interaction has gained interest for HCI researchers studying UX. Instead of considering experience only in terms of an individual's reaction, they extend it to something constructed in social interaction. Battarbee [2003] introduced the term "Co-experience" for *the experience that users themselves create together in social interaction.* According to the author, the design of technology should be oriented toward the understanding of people's interactions and collaborations; more precisely, "*how people make distinctions and meanings, carry on conversations,*

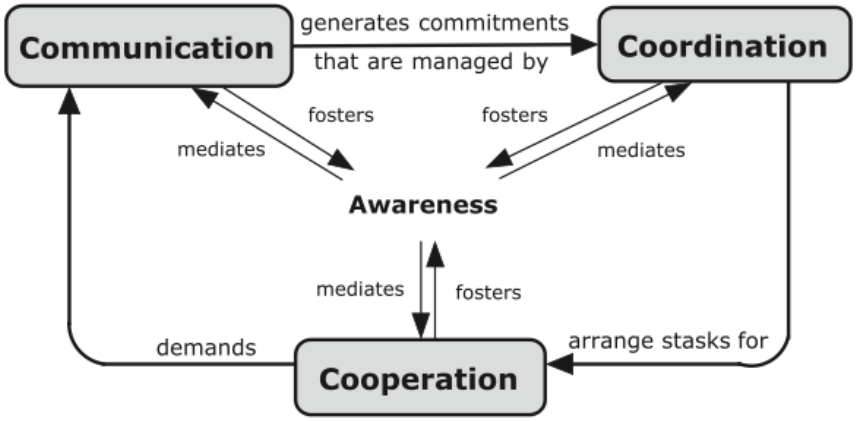


Figure 2.7.: 3C collaboration model defined in [Fuks et al., 2005]

share stories, and do things together". Often relying on Dourish [2004] the concept of embodied interaction, other researchers have studied how technology can influence social interactions. For instance, Hornecker and Buur [2006] proposed a framework to better understand the social user experience of tangible interaction and provide perspectives for designing to support social interaction and collaboration. Gaver [1996] explored social interaction from an ecological perspective, *using the concept of affordances to describe material properties of the environment that affect how people interact.* Relying on technologies that support collaboration, the author define affordances for sociability as the possibilities offered by the technology for social interaction. Finally, applied to collaborative learning, Kreijns et al. [2003] argue that research should focus on guiding the design of sociable environments, providing support for communication "*through the inclusion of persistent presence and awareness through time and space of the other members of the distributed learning group*".

2.4.2. Collaboration

The broad definition of collaboration corresponds to the process of individuals working together to achieve a common goal.

The 3C model of collaboration, first proposed by Ellis et al. [1991] and then improved by Fuks et al. [2005], considers collaboration as the combination of communication, cooperation, and coordination among participants. This approach is commonly shared by Computer Supported Collaborative Work (CSCW) researchers such as Grudin and Poltrock [1997]. Communication involves exchanging messages and information among individuals. Coordination deals with the management of people, their activities, and resources. It happens before cooperation by identifying goals and planning tasks, during the cooperation by monitoring tasks carried out , and after cooperation by evaluating tasks. Finally, cooperation involves joint production occurring within a shared information space, such as producing, manipulating, and organizing information. The three processes strongly rely on mutual awareness. Indeed, awareness information is essential to create a shared context and to interpret the intentions of the group members.

Collaboration is also widely studied in the field of Education. Collaborative learning is defined as *a situation in which two or more people learn or attempt to learn something together*

[Dillenbourg, 1999]. In his definition, Dillenbourg [1999] insists on the importance of the monitoring and regulation of interactions, the sharing of goals, and the division of labour. These aspects are related to previously defined coordination mechanisms. According to the author, the difference between collaboration and cooperation lies in the degree of labour division and the type of communication. In cooperation, group members split the work and carry out tasks individually, using asynchronous communication, whereas in collaboration, group members carry out tasks together, requiring synchronous communication.

In CSCW and HCI, researchers are investigating how technology can foster collaboration, focusing on specific processes or mechanisms. For instance, Fuks et al. [2005] highlight the importance of identifying relevant awareness information and how to display it in the digital environment. The concept of awareness is widely investigated from a multi-user interfaces perspective [Dourish and Bellotti, 1992; Gutwin and Greenberg, 2002; Hornecker et al., 2008; Yuill and Rogers, 2012]. In CSCL, empirical research has shown evidence on the role of regulatory processes in learning performances, and different studies investigate how to support regulation with technology [Järvelä and Hadwin, 2013]. Finally, different works study how to support communication through different modalities [Oh et al., 2018], informal communication [Mackay, 1999] , and information sharing [Scott et al., 2003]. Discussions and information sharing are aimed at building a common ground, which means that group members collaborate in ensuring understanding and ground their mutual knowledge and assumptions [Clark and Brennan, 1991].

In the following section, I will detail the first two mechanisms, awareness and regulation.

2.4.3. Awareness

Definition

In HCI, many researchers have explored the concept of awareness when using digital environments [Markopoulos and Mackay, 2009]. Endsley [1995] defined the concept of *situation awareness* as *knowledge created through interaction between an agent and its environment, in simple terms, "knowing what is going on"*. Relying on this work, Gutwin and Greenberg [2004] identify four characteristics of awareness:

- Awareness is knowledge about the state of an environment bounded in time and space.
- Awareness is knowledge that must be maintained and kept up to date because environments are changing over time.
- Maintaining awareness is done through the interaction of people exploring the environment.
- Maintaining awareness is done to complete some task in the environment (which is the main goal).

Awareness is frequently associated with coordination. According to Dourish and Bellotti [1992], *awareness is an understanding of the activities of others, which provides a context for your own activity.* The authors underline the importance of awareness for coordination of activities and sharing of information that will lead in turn to successful collaboration. In particular, they make a distinction between awareness of the character of actions (which allow participants to structure their activities and avoid duplication of work) and the content of action (which allows fine-grained shared working and fosters synergistic group behavior). Fuks

et al. [2005] emphasize that coordination is *contextually established and strongly dependent on mutual awareness* since it is useful for detecting changes in plans and understanding and monitoring the completion of tasks.

Based on these broad definitions, various variations of the concept have been proposed in the literature. For instance, Macmillan et al. [2004] proposed a model of *mutual awareness* defined as three interrelated facets: taskwork awareness (tasks completed by other group members and their importance), workload awareness (loading imposed by the tasks on group members), and teamwork awareness (coordination and back-up between group members). Gutwin et al. [1996] identified four types of awareness for face-to-face collaboration in the literature: informal, social, group-structural, and workspace awareness. *Informal awareness* refers to the general sense of who's around and what they are up to. It can be linked to the sense of social presence. *Social awareness* indicates a person maintaining awareness about others in a social or conversational context, using conversational and non-verbal cues. *Group-structural awareness* refers to knowledge about group members' roles and responsibilities. Finally, *workspace awareness* is the most frequently used concept for co-located collaboration settings and multi-surfaces or distributed environments. Based on several works such as Dourish and Bellotti [1992]; Beaudouin-Lafon and Karsenty [1992], Gutwin et al. [1996] defined workspace awareness as *the up-to-the-moment understanding of another person's interaction with the shared workspace*. It corresponds to how people interact with the workspace, limited to events happening in the temporal and physical bounds of the collaborative activity [Gutwin and Greenberg, 2002].

Supporting awareness

The various works underline the fact that technology can make awareness mechanisms less effective, due to the limitation of making information available to sensory organs [Fuks et al., 2005] and interfering with people's perception [Gutwin and Greenberg, 2002]. Information may not be available in the environment or may be in an inappropriate form to maintain a good level of awareness. Conversely, technology can also help in filtering irrelevant information, reducing distractions that usually affect face-to-face collaboration [Fuks et al., 2005]. Fuks et al. [2005] and Gutwin and Greenberg [2002] commonly argue that designers of collaborative environments should identify relevant awareness information, determine how to gather this knowledge, determine when and where the knowledge will be used, and how to display it.

In early research on awareness, Dourish and Bellotti [1992] proposed a shared feedback approach consisting of presenting information on group members' activities within a shared workspace, supporting passive awareness mechanisms and improving dynamic coordination. Since then, various awareness tools have been investigated in the literature [Gutwin and Greenberg, 1998; Nova et al., 2007; Janssen et al., 2011]. Buder [2011] identify several challenges in supporting two main activities related to awareness identified by Schmidt [2002] : displaying (related to the process of making something aware) and monitoring (related to the process of actually becoming aware of information that was displayed by others before).

From a methodological perspective, Gutwin and Greenberg [2002] elaborate on a conceptual framework to guide the design of workspace awareness support in collaborative environments. The framework describes three aspects of workspace awareness: its component elements, the mechanisms used to maintain it, and its uses in collaboration. They structure the

different types of awareness information according to who are working (presence, identity, authorship), what they are doing (action, intention, artifact), where they are working (location, gaze, view, reach), when events happen (event history), and how those events occur (action history).

Measuring awareness

According to Hornecker et al. [2008], there is a lack of empirical evidence or measures to investigate the ability of technology to support awareness, mainly due to the poor operationalization of the concept. In their study, they identify several approaches to measure awareness. Behavioral measures are rarely employed, and most works use indirect subjective measures, such as measuring social presence [Harms and Biocca, 2004], perceived effort, or satisfaction [Gutwin and Greenberg, 1998; Ha et al., 2006] , as well as direct subjective measure of mutual awareness [Macmillan et al., 2004] , which measures the three aspects of their model.

For instance, Gutwin and Greenberg [1998] investigated the impact of awareness information visualization using time completion and analyzing verbal communication among group members. They showed that workspace awareness information can reduce completion time, improve communicative efficiency, and increase satisfaction. In their study, Ha et al. [2006] analyzed awareness of both intention and action through logs analysis (collision for awareness of intention and amount of time taken to respond to a partner's action for awareness of action) and interviews. They underlined the difficulty in finding appropriate measures for awareness of intention and argued that more research should be conducted to specify relevant measures.

From their analysis of the literature, Hornecker et al. [2008] derived different categories of workspace awareness indicators available from both logs and video analysis. They define positive awareness indicators such as reactions without explicit requests, the amount of parallel work, and complementary actions on the same activity without verbal coordination. They also introduced negative awareness indicators such as interference , with collisions and breakdowns commonly interpreted as a sign of lack of awareness (as done in [Ha et al., 2006]). As suggested by Schmidt [2002], verbal monitoring can also represent a low level of awareness, forcing people to use explicit mechanisms of coordination or to explain rationale of past actions. They finally define a third category, awareness work indicators, for practices aiming at increasing the level of awareness such as verbal shadowing to keep up-to-date group members.

2.4.4. Regulation

Definition

Regulation processes are a key aspect of collaborative activities, especially in learning activities. Järvenoja et al. [2020] argue that "*regulation activities cover a wide process, where cognition, emotion, motivation, and behavior are adapted according to the aims, goals, and standards of both the individuals and the group*". Thus, regulation requires processes to plan, monitor, and evaluate the joint activity [Vauras et al., 2003]. In the field of CSCL, it is commonly accepted that there are three types of regulation: self-regulation, co-regulation, and social regulation [Hadwin et al., 2011].

Self-regulation refers to the process by which learners activate and sustain cognition, affect, and behaviors oriented toward the accomplishment of learning goals [Schunk and Zimmerman, 2008]. Self-regulation processes provide learners with information and indicators on their actions or progress. This reflexivity then leads them to change their behavior, motivation, or even their understanding of the subject. Hadwin et al. [2010] indicate that even if self-regulation is an individual-centered process, there is an important social aspect [Hadwin et al., 2010].

Co-regulation refers to the transitional process in a learner's acquisition of self-regulation through the interactions between a student and an expert, or a more experienced individual [Hadwin et al., 2010]. Sharing a common problem -solving plan, self-regulation is gradually appropriated by the learner thanks to their interactions. More recent definitions indicate that with a co-regulation system, each member may be prompted to modify another group member's regulation process to help them progress or to advance the group towards its final goal [Järvelä and Hadwin, 2013].

Finally, socially shared regulation refers to the processes by which multiple group members regulate their collaborative activity [Hadwin et al., 2010]. Järvelä et al. [2016] indicate that *"this type of regulation involves interdependent or collectively shared regulatory processes, beliefs, and knowledge (e.g., strategies, monitoring, evaluation, goal setting, motivation, and meta-cognitive decision making) orchestrated in the service of a co-constructed or shared outcome"*. From this perspective, collaboration is supported through co-constructing knowledge and co-solving a problem, and it requires developing a shared awareness and mutual understanding of goals, progress, and tasks [Hadwin et al., 2010].

Supporting regulation

CSCL research has gained interest in developing technological tools for supporting, prompting, and scaffolding regulation [Järvelä and Hadwin, 2013]. Several trends have emerged to support shared regulation, including supporting group awareness and sociability [Järvelä et al., 2015]. In many studies, promoting awareness is a way of supporting regulatory processes. For instance, Kirschner et al. [2015] evaluated two tools (Radar and Reflector) designed to enhance awareness of group members' social and cognitive behaviors by eliciting information from group members on social and cognitive behaviors. Their results showed that the tools led to higher levels of group satisfaction, lower levels of conflicts, and higher social group performance. Järvelä et al. [2015] identified three design principles to support social shared regulation: (1) increasing learners' awareness of their own and others' learning processes, (2) supporting the externalization of students' and others' learning processes and helping in sharing and interaction, and (3) prompting the acquisition and activation of regulatory processes. They implemented these principles in an extended version of Radar, and their results showed that the tool supports not only socially shared regulation but also collaborative learning.

In terms of design, supporting regulation implies providing individual or collective feedback in real time about the ongoing collaborative activity. DiMicco et al. [2004] have shown the potential of displaying these indicators in real time. Several projects are exploring the integration of these indicators into the digital environment using visualisations based on metaphors. To regulate discussions among group members during collaborative activities on tabletops, several studies use abstract forms to represent speakers' participation [Bachour et al., 2010; DiMicco et al., 2004]. For instance, DiMicco et al. [2004] explored dynamic

awareness displays revealing speaker participation patterns, updating the size of coloured circles representing users as a function of their absolute or relative speaking time in relation to a group during a discussion. Their results showed that these displays influenced the amount of participation of individuals in a discussion and the process of information sharing used during a decision-making task. Järvenoja et al. [2020] implemented and evaluated a regulation tool (S-REG tool) to investigate when and how students activate co- and socially shared emotion and motivation regulation in collaborative learning. The tool supports group members' awareness of the motivational, emotional, and cognitive states of the collaborative learning, and prompts groups to activate appropriate group-level regulation to respond to the group's situational needs. The indicators are visualised using a traffic light metaphor (green if everything is fine, yellow for an unclear situation, and red for severe challenges and need for regulatory actions).

Measuring regulation

Measuring regulation raises several challenges. First, as awareness and regulation are closely related when designing environments supporting regulation, the boundary between the two concepts is also thin when analyzing collaboration. For instance, verbal monitoring (which means one asking another what they are doing) is defined as an awareness indicator by Hornecker et al. [2008], whereas it could also be used for regulation. Second, as highlighted by Järvelä et al. [2021], regulation requires mental processes and there is a challenge in developing methods that make these invisible processes observable and thus measurable. Finally, regulation processes are affected by conditions that change over time and measurement approaches should consider these dynamic aspects.

Regarding the methods employed to measure regulation, self-reporting instruments have been used but frequently without contextualizing the regulation processes [Järvelä et al., 2016]. In addition, learners' perceptions often do not align with what actually occurred during learning [Järvelä et al., 2021]. Video encoding is the other subjective approach frequently used to analyze regulation. For instance, Rogat and Linnenbrink-Garcia [2011] proposed a video coding protocol for analyzing social regulation in collaborative activities, which is also used by Evans et al. [2016] when studying students' collaborative learning processes around a tabletop in an ecological classroom setting. They analyzed social regulation with three categories including planning (distinguishing task planning and content planning), monitoring (monitoring content, plan, and progress), and behavioral engagement (encouraging an off-task group member to re-engage, reminding a group member to return to task). Some work criticizes this approach for relying on the subjective coder's interpretation of observed behavior.

Finally, Järvelä et al. [2021] propose to triangulate multiple sources of data to overcome the methodological weaknesses of previous approaches. They illustrate how multimodal data (including behavioral and physiological data) can be used to identify markers that characterize successful learning regulation and learning progress. This approach combining behavioral analysis with other sources of data was already proposed by Winne et al. [2010] who developed a software (gStudy) aimed at promoting self-regulated learning and collecting observable traces of learners' uses of strategies during complex collaborative tasks. Finally, to tackle the challenges related to the fact that regulation processes are affected by conditions that change over time, Järvelä et al. [2016] propose to implement sequential and temporal aspects in the data analysis.

3. Analyzing User Behaviors to Support Collaboration and Social User Experience in Multi-Surfaces Environments

This chapter contributes mainly to my Research Axis 1, which consists in *observing and understanding users' activities and experiences with technology to inform the design.* In this chapter, I focus on collaboration in Multi-Surface Environments (MSE). We proposed models and methods to analyze collaboration, and we relied on empirical approaches, conducting situated studies and lab experiments, to assess the impact of technology on collaborative behaviors. This led to methodological and empirical contributions. We also developed several prototypes combining devices for supporting both individual and collective activities, leading to technical and design contributions (Research Axis 3).

3.1. Challenges in Supporting Collaboration in MSE

Multi-Surface Environments (MSE) are particularly suited for conducting complex collaborative problem-solving activities involving rich data exploration. Examples range from games [Döring et al., 2010; Scott et al., 2014b], urban planning [Sugimoto et al., 2004], as well as emergency response planning [Chokshi et al., 2014]. In Education, complex learning scenarios mixing personal and collaborative activities are considerably increasing [Dillenbourg and Tchounikine, 2007] and can benefit from MSE. Former studies have shown that using tabletops in collaborative learning activities promotes higher levels of thinking and more effective work [Dillenbourg and Evans, 2011; Kharrufa et al., 2013; Higgins et al., 2012]. According to Yuill and Rogers [2012], multi-user surfaces enhance awareness compared to other input devices. Collaborative decision-making applications can leverage tabletops' properties: promoting equal access to all group members, and direct interaction with digital information displayed on an interactive surface [Rogers and Lindley, 2004; McCrindle et al., 2011].

However, supporting analytical individual tasks or the development of personal judgments should be further explored in these shared environments [Pinelle et al., 2003; Gutwin and Greenberg, 1998]. According to Dillenbourg [1999], collaborative activities are enhanced when learners have both individual and collective workspaces. Introducing personal devices, such as tablets, can be helpful to address this issue. For instance, in Caretta [Sugimoto et al., 2004], groups of students work together on urban planning tasks with a shared surface combined with several PDAs. The shared surface supports the city construction, on which students can manipulate physical objects and make decisions on the city's evolution. PDAs are used as personal spaces where students can experiment with ideas running simulations on different parts of the city. When looking at devices independently, commonly held views

are that: (1) large shared surfaces are well-suited for complex tasks [Liu et al., 2014] and for co-located collaborative activities [Zagermann et al., 2016; Higgins et al., 2012]; (2) tabletops enable more equitable participation [Scott et al., 2003] and awareness [Yuill and Rogers, 2012]; and (3) handheld devices support mobility with pervasive access to information, support planning, and enable monitoring of activities [Sugimoto et al., 2004].

Yuill and Rogers [2012] distinguish three mechanisms accounting for the success of multi-user surfaces: high awareness of others' actions and intentions, high control over the interface, and high availability of background information. They argue that "*this requires consideration of orientation of display, presence of personal "territories" for users, size of surface in relation to users, amount of information a user is able to apprehend, possibility of users interfering with each other's awareness, and the role of personal technologies that might require sharing, or might inhibit mutual awareness*". Awareness and regulation are often considered together since researchers in CSCW argue that supporting awareness facilitates coordination of collaborative activities and communication between group members [Gutwin and Greenberg, 1998; DiMicco et al., 2004; Williams et al., 2005; Markopoulos and Mackay, 2009]. From this statement, we derive three challenges.

First, the multiplication of devices and spaces may make awareness and regulation mechanisms more difficult to maintain than in other settings. Personal devices bring mobility among group members that did not exist in tabletop settings. This can lead to dynamic configurations that can disrupt the awareness of what the other group members are doing or which objects are manipulated or transferred from one device to another. Some researchers investigate how to support awareness in MSE such as MacKenzie et al. [2012] who proposed to show active personal devices on the shared public space, or Scott et al. [2014b] who proposes to visualize feedback during object transfer to increase awareness. Sharing information and transferring objects are often related to cross-device interaction [Döring et al., 2010; Seyed et al., 2012; Marquardt et al., 2012; Brudy et al., 2018]. For instance, Seyed et al. [2012] present an overview of the main gestures for cross-device interaction. They classify the gestures according to the specific actions required in a multi-display environment. They analyze interactions between collaborative devices (tabletop, digital board, etc.) and personal devices (tablets, mobile phones, etc.). In terms of information available, Scott et al. [2004] propose the concept of territoriality on the shared tabletop workspace, including personal, group, and storage territories. Relying on this concept, Scott et al. [2014a] extend the concept to multi-device environments and propose a virtual bridge between devices to transfer information between tabletops and tablets without user identification. Personal areas displayed on the tabletop (representing the bridges) allow each user to move information from the tabletop to his/her tablet, by dragging and dropping this information onto his/her bridge area. In their study, they showed that the use of virtual bridges helped to maintain a certain level of awareness.

The variety of devices and combination in MSE makes the question of how to support effective collaboration in such environments still open. Designing collaborative activities in MSE raises several complex issues such as supporting awareness and regulation for the group, or sharing and exchanging information between devices. Empirical studies are also needed to investigate the impact of such environments on behaviors and collaboration.

Secondly, Yuill and Rogers [2012] underline the importance of considering orientation and sizes of surfaces. The form factor, i.e., size, orientation, overall shape, and configuration of surfaces in a MSE are generally decided early in projects. Yet, these factors shape the affordances of devices and thus can have impacts on how people interact in these environments. For instance, large screens afford a shared vision of the task and tend to encourage

people to interact together [Ryall et al., 2004]. However, Zagermann et al. [2016] recently showed that as the size of tabletops increases, collaboration quality or sense-making results decreases, since the larger screen diverts users' attention away from their collaborators and towards the shared display. Inkpen et al. [2005] investigated display orientation, size, and user arrangements. They found that although participants felt the horizontal display was more natural and comfortable for collaboration, working with a vertical display tended to be more time-efficient. Rogers and Lindley [2004] were among the first to study the impact of device orientation on interaction and collaboration. They showed that horizontal displays are better at supporting collaboration, as they promote more suggestions and idea generation, but also lead to more role switches and greater awareness of others' actions. Potvin et al. [2012] compared vertical and horizontal multi-touch displays and found that the horizontal surface encouraged equal physical interactions with the display, as well as equal verbal participation. However, these studies were focusing on a single screen. Since Rogers and Lindley [2004]'s study, large multi-touch displays, smartphones, and tablets have become pervasive, raising the question of how people will behave and collaborate in such MSE.

Collaboration can be fragile and influenced by small details such as devices configurations, in particular display orientation. Thus, there is a challenge in investigating how form-factor and set-up configuration in MSE shape collaboration.

Thirdly, the use of personal devices in MSE configuration introduces mobility for both people and devices. As underlined by Marshall et al. [2011], ubiquitous technologies transform physical spaces, encouraging particular kinds of social interactions and shaping group organization in collaboration. Some works rely on the concept of micro-mobility [Luff and Heath, 1998] to investigate personal territoriality or to allow objects sharing or transfers. For instance, Marquardt et al. [2012] propose cross-devices interaction by leveraging the proxemics of devices and people. To analyze spatial configurations of a group, these works rely on the description of spatial patterns formed during face-to-face interactions between two or more people (F-formations defined by Kendon [1990]). For instance, Marshall et al. [2011] showed how F-formations (or their absence) can be used to explore the influence of the physical environment on co-located interactions.

An important challenge highlighted by the literature is to better understand at a fine-grained level how technology shapes collaboration and therefore to develop tools to make these observations easier. In particular, it seems interesting to observe physical arrangements of group members when introducing mobile devices and their impact on collaborative behaviors.

To tackle these challenges, we studied different MSE form-factors and configurations for collaborative learning activities. We explored simple setups with only one tabletop [Lachand et al., 2016] and different MSE: combination of tabletop and tablets [Tong et al., 2017a,b], combination of mobile devices only for outdoor settings [Tong et al., 2016], and combinations of tablets for class settings [Lachand-Pascal et al., 2022]. To observe social interactions and collaborative behaviors, we specified a model of collaboration and a method to describe collaborative behaviors, spatial configuration, and devices usage (described in section 3.2). Then we designed several prototypes exploring how to support different key elements in collaboration such as awareness and regulation, information sharing, and territoriality aspects. Finally, we conducted different studies to analyze the impact of these affordances on collaboration (described in section 3.3).

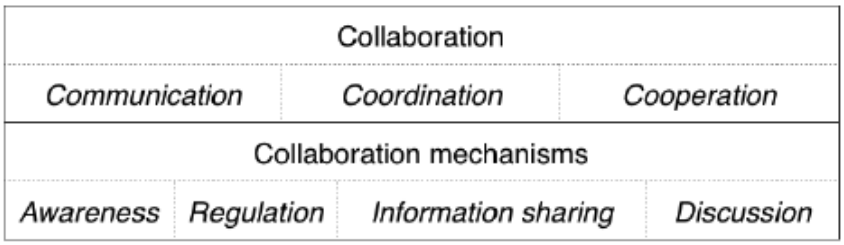


Figure 3.1.: The hierarchical model of collaboration defined in [Tong, 2017]

3.2. Observing users behaviors in collaborative environments

This research was conducted through the supervision of several M2 Research projects and mainly during the co-supervision of Lili Tong's PhD with Sébastien George (LIUM - Université du Mans) and Aurélien Tabard (LIRIS-SICAL), funded by the China Scholarship Council PhD program and in part by the ANR JENLab project. During Lili's PhD [Tong, 2017], we proposed a collaboration model and we referenced indicators used in the literature into an analysis grid to analyze collaboration mechanisms when using technology, in particular for co-located collaboration on tabletops or MSE (presented in section 3.2.1). In addition, we proposed a method to analyze collaboration mechanisms and device usage through the lens of group spatial configurations, using f-formations (presented in section 3.2.2). This work was published at the conference MobileHCI 2016 [Tong et al., 2016] and in the "Interaction Techniques for Mobile Collocation" workshop held at the same conference [Serna et al., 2016]. The model and method were then used in several studies to analyze collaboration [Tong et al., 2017a,b] (presented in section 3.3).

3.2.1. Collaboration model and indicators

We synthesized previous models described in section 2.4 in the theoretical foundations chapter 2 to propose a hierarchical model helpful to analyze collaboration in MSE, illustrated in Figure 3.1.

The top layer is collaboration and its three areas: **coordination**, **cooperation**, and **communication**, as defined in Fuks et al. [2005]'s model of collaboration. **Coordination** concerns the management of participants, their activities, and resources [Ellis et al., 1991]. In coordinated work, participants act towards a shared goal dealing with time and organizational constraints [Malone and Crowston, 1990], but their individual actions are only externally related to each other. **Cooperative work** is accomplished by the division of labor among participants. Participants act towards a shared goal, but each performs specific and independent actions to achieve part of the overall goal [Bardram, 1998]. **Communication** is related to the exchange of messages and information among people to reconceptualize their own organization and interaction toward their shared goal.

These three areas are too high-level to effectively guide collaboration analysis. Thus, to understand concrete collaborative behaviors, we decided to include a lower layer in the model, containing the core mechanisms defined in the literature (section 2.4): **awareness**, **regulation**, **information sharing**, and **discussion**. **Awareness** involves knowledge of what

others are doing, and how it fits within the larger activity. Awareness covers both high-level tasks, but also knowledge of physical and spatial arrangements of other participants [Gutwin and Greenberg, 2002; Gutwin et al., 1996]. **Regulation** builds upon awareness and relates to people's ability to plan, monitor, evaluate, and regulate the joint activity [Vauras et al., 2003; Volet et al., 2009]. **Information sharing** involves building a common ground [Clark and Brennan, 1991], with people ensuring a shared understanding, mutual knowledge, and assumptions. It also involves sharing information on physical objects such as documents and materials. Finally, **discussion** is required to reach a decision and is considered as the process of talking among people to exchange ideas and reach a consensus based on the information available.

These four mechanisms can be analyzed as standalone behaviors. They can also be considered as interlaced or consequential behaviors, as one mechanism could lead to another (e.g., a good level of awareness may cause regulation and discussion). To observe these behaviors, we referenced indicators commonly used in the literature for each mechanism. These indicators correspond mainly to observations of group participants from video analysis. For instance, table 3.1 presents the grid for awareness analysis and table 3.2 the indicators for discussion. The analysis method that we proposed consists of selecting the most appropriate indicators from the grid, then supplementing them with indicators from data logs. We did not represent data log indicators directly in the grid since they are usually task -dependent. Table 3.3 presents the analysis grid used in the study published at Interact 2017 [Tong et al., 2017b] (and described in section 3.3.2) to analyze the impact of MSE configuration on collaboration.

3.2.2. Spatial configurations using F-formations

To study the mobility brought by personal devices in MSE configuration, we explored the use of a combination of mobile devices in highly mobile conditions. Mobile devices are especially interesting in their ability to provide digital information while still supporting social interactions between group members, which are essential elements of coordinated and shared activities. However, in truly mobile conditions, e.g., outdoors, the high variability of groups' spatial configurations can potentially modify collaboration mechanisms. In Tong et al. [2016], we analyzed the relationship between participants' spatial configurations, their device usage, and collaboration mechanisms (the four mechanisms in our model: awareness, regulation, information sharing, and discussion). To analyze people's spatial-orientational arrangements in joint activities, we used Kendon's F-formations [Kendon, 1990] with a focus on how F-formations are created during the collaboration and what are the social interactions that occur within these arrangements.

F-formations

F-formation is a term and system devised by Kendon [1990] to describe how people adjust their position and orientation to interact together and jointly manage their attention. Inside F-formation arrangement, three different spaces are distinguished: an internal interactional space where explicit actions are carried out, the space occupied by the participants themselves, and the surrounding space, which can be considered as a kind of buffer between the group and the outside world. Kendon [1990] described three types of F-formation for groups of two persons: L-shaped, face-to-face, and side-by-side (see Figure 3.2, top), and he added

Data source	Categories	Indicators	Ref
Video	Negative	Interference / Collisions	[Hornecker et al., 2008]
		Verbal monitoring	
		Long time taken to respond to a partner's action	[Ha et al., 2006]
	Positive	Reaction without request	[Hornecker et al., 2008]
		Parallel work	
		Complementary actions	
		Object handover	
		Focuses on shared surface	[Rogers and Lindley, 2004]
		Short time taken to respond to a partner's action	[Ha et al., 2006]
	Awareness work	Verbal shadowing	[Hornecker et al., 2008]
		Raise voice and speak loud	[Rogers and Lindley, 2004]
		Body movements (turn to face to others; peer over shoulders; move to display)	
Questionnaire & Interview	How aware participants were of their partners' actions? How aware they felt their partners were of their own actions? How well the different techniques helped participants stay aware of others' actions?		[Bachl et al., 2011] [Pinelle et al., 2008] [Wallace et al., 2009] [Zagermann et al., 2016]

Table 3.1.: Indicators for analyzing awareness defined in [Tong, 2017].

Categories	Indicators	Ref
Nature of discussion	Negotiating	[Forlines et al., 2006]
	Making/accepting/rejecting suggestions	
Acts of discussion	Number/duration of utterances	[Rogers and Lindley, 2004] [Seifert et al., 2012] [Potvin et al., 2012]
	Speaking turns	[Marshall et al., 2008]
	Proportion of speaking time	[Potvin et al., 2012]
	Gesture or interaction on devices	[Forlines et al., 2006]

Table 3.2.: Indicators for analyzing discussion defined in [Tong, 2017].

Behaviors	Data source	Indicators	
Interaction with devices (H1 & H2)	Log	Notes / Favorite locations / Total number of touch events	
	Video	Touches on shared display per participant	
Awareness (H3)	Video	Positive	Reaction without request / Complementary action
		Negative	Interference / Verbal monitoring
		Neutral	Verbal shadowing
Activity organization (H4)	Log	Locations checked together at the same time / Locations checked per person	
	Video	Discussion on strategy / Duration of the whole task	
Discussion (H5)	Video	Discussion on hotels, attractions, budget and itinerary / Sharing tablets for discussion	

Table 3.3.: Analysis grid used in [Tong et al., 2017b].

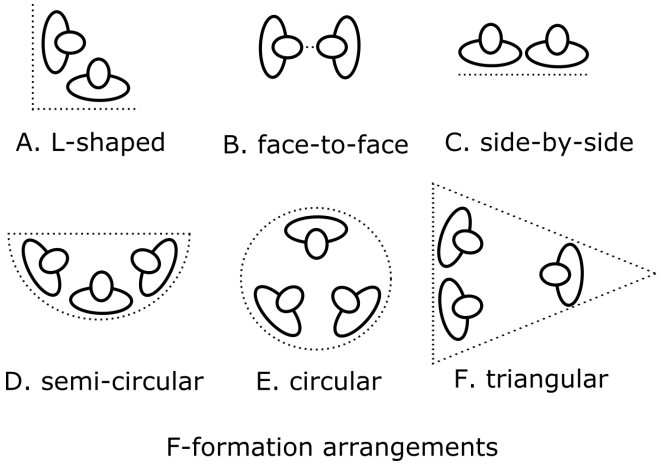


Figure 3.2.: F-formations arrangements used in [Tong et al., 2016].

a circular F-formation arrangement for groups of more than two persons. Marshall et al. [2011] added two more arrangements for groups of four persons: semi-circular and rectangle. F-formations have been used in former research to describe social interactions [Marshall et al., 2011], or can also lead to new multi-device interaction techniques [Marquardt et al., 2012].

Analysis method

We co-designed with teachers an orienteering mobile learning game using multiple mobile devices in outdoor settings. We conducted a study that involved four groups of three students, all equipped with tablets. During the experiment, one teacher and one person from our research team followed each group to supervise and film the group activity.

We adopted a qualitative approach through the analysis of recorded videos. We analyzed



Figure 3.3.: A sequence of collaborative behaviors and their corresponding F-formations described in Tong et al. [2016]. A: Sophie is scanning a QR code, David and Anna are watching (awareness); B: Sophie reads out code to others (verbal information sharing); C: David and Sophie move towards Anna to see her tablet (awareness & regulation); D: Sophie takes Anna's tablet (on-device information sharing); E: Sophie holds up her tablet showing it to the others (on-device information sharing); F: They are discussing the puzzle (discussion); G: David double checks the tablet (on-device information sharing); H: During the discussion, Anna suggests to move forward (discussion & regulation); I: Sophie asks David where to go next (regulation & on-device information sharing).

students' gazes, gestures, and conversations to identify the collaboration mechanisms. Then, we focused our analysis on whether some mechanisms led participants to position or orient themselves in specific arrangements; we also looked more precisely into tablet use and micro-mobility. To do so, two researchers scripted in detail the video segments to document the relevant F-formations and the use of tablets (number of tablets used and their orientation according to users) for each identified mechanism. Finally, we analyzed in detail one sequence involving all the collaboration mechanisms identified and the transition from one to the next. Figure 3.3 shows the most representative formations. To describe the dynamic of F-formations for this particular sequence, we counted their occurrence, transition, and duration.

Results

In our study, the groups consisted of three students. We noticed three main types of F-formation arrangements: semi-circular, circular, and triangular (see Figure 3.2, bottom). These arrangements can be influenced by the ongoing task and also by environmental features. Given the mobile nature of the activity, compared to the F-formations described in the HCI literature, the F-formations we observed were highly dynamic. Both within the formation, for example, students would keep their formation but move in the same direction, or all rotate at once and also moving quickly from one formation to another. A transition from one formation to another often indicated a change of the focus in the ongoing task. It could

be also due to changes in awareness levels. The circular arrangement was the most stable formation we observed, and also the most frequent one, especially for discussion. We observed that regulation behaviors mostly happened within dyads. L-shaped or side-by-side arrangements were mostly used when participants needed to refer to devices, focusing in such cases on the same device. Face-to-face F-formations were used when the regulation mechanism did not require a device. Finally, in the semi-circular arrangement, three students stay corner-to-corner, which allows them to easily share objects such as a tablet or an instrument (information sharing).

3.2.3. Summary of contribution

This section describes mainly methodological contributions for the observation of collaboration in multi-surface environments. From the existing literature, we proposed a model of collaboration with four mechanisms (awareness, regulation, discussions, and information sharing) that can guide the analysis of collaboration by picking the indicators most relevant to the context. In our method, we recommend combining these indicators with data logs analysis. We did not integrate log indicators directly since they are usually task-dependent. We also propose to complement these indicators with a description of spatial arrangements and device usage for each collaborative mechanism, relying on the F-formation framework. Our qualitative study presented in [Tong et al., 2016] offers insights on how students use tablets to collaborate in mobile settings and the importance of transitions between arrangements (more important than F-formations per se). These observations allowed us to derive implications for design, in respect to complex information sharing, regulation, and control in proxemics interaction in mobile conditions.

3.3. Designing Technology Affordances for Collaboration and Understanding their Impact on User Behaviors

As identified in the challenges, designing collaborative activities in MSE should integrate features to support awareness and regulation for the group, and sharing and exchanging information between devices. During the projects in which I was involved, we developed several prototypes to explore how to support these key elements in collaboration. We then conducted studies to investigate the effects of these affordances on user behaviors to inform the design of such technologies.

For instance, in Marty et al. [2016], we extended the concept of territoriality implemented by Scott et al. [2014a] to explore territory arrangement on the different devices, inter-territory actions to manage information, and contextual information visibility for objects involved in the learning tasks. In Lachand-Pascal et al. [2022], we explored interaction strategies to perform content sharing and remote control tasks in classrooms composed of heterogeneous devices, ranging from personal computers to tablets, smartphones, and video projectors.

In this section, I detail three prototypes providing affordances for collaboration and their impact on user behaviors. Section 3.3.1 presents Pickit, a tool supporting collaborative decision-making activities in MSE combining a shared surface and mobile devices. We ran a situated study to understand its effect on collaborative behaviors and on the learning decision-making process [Tong et al., 2017a]. In section 3.3.2, we explore the impact of

devices ' form factors and configuration on collaboration in a laboratory study using a modified version of Pickit [Tong et al., 2017b]. Lastly, in section 3.3.3, we investigate how to design reflexive indicators to support social regulation on tabletops with a laboratory study [Lachand et al., 2016].

3.3.1. Supporting Collaborative Decision-Making Activities

In Tong et al. [2017a], we explored how technology, and more specifically MSE, can support the learning decision-making process. Educators have emphasized the importance of collaborative decision-making skills in scientific education [Ratcliffe, 1997; Grace, 2009; Evagorou et al., 2012], arguing that these skills facilitate effective knowledge acquisition among students. Collaborative decision-making becomes even more relevant in multi-disciplinary education, such as when educators tackle socio-scientific issues [Evagorou et al., 2012], e.g., sustainable development.

Decision-making is a process of gathering information, identifying and weighing alternatives, and selecting among various alternatives based on value judgments [Uskola et al., 2010]. Several models of decision-making processes have been introduced in the learning literature over the past years [Janis and Mann, 1977; Ratcliffe, 1997; Roberto, 2009]. These models differ mostly in how they scope the decision-making process. They define, however, similar stages and all underline the non-linear nature of the process. The most generic model, proposed by Ratcliffe [1997], consists of 6 stages that can be intertwined: 1) Listing options; 2) Identifying criteria; 3) Clarifying information; 4) Evaluating the advantages and disadvantages of each option according to the criteria previously identified; 5) Choosing an option based on the analysis undertaken; 6) Evaluating the decision-making process, and identifying any possible improvements.

The literature emphasizes that students struggle with such complex issues, especially with multi-dimensional analyses. The underlying problems lie in difficulties to: become familiar with the material, evaluate choices and reach a decision together, follow a process, know what others are doing, and adjust behavior accordingly. To improve students' ability to make decisions, it is necessary not only to focus on the result of their discussions but also on how the students carry out the decision-making process, such as how they are able to evaluate and take into account the available information individually [Uskola et al., 2010]. Learning environments supporting decision-making processes should enable both collective and individual activities, including exploring and analyzing data, modeling, voting, or analyzing decisions.

Affordances Design

We decided to focus on supporting the analytical process related to decision-making (stage 3, 4, and 5 of Ratcliffe [1997]). We identified four broad categories of behaviors relevant to decision-making activities, based on the literature and on our model of collaboration described in section 3.2.1: exploring content, discussing options, maintaining group and activity awareness, and regulating the activity.

The prototype developed, named Pickit, uses a combination of a tabletop and tablets to support the analytical decision-making process. The tabletop is mostly dedicated to viewing the decision-making context (figure 3.4(b)), and the tablets are dedicated for browsing the

options (figure 3.4(c)). We introduced several features to foster awareness and facilitate group regulation. For example, when a student picks a location to explore, the background color of his/her avatar on that option card will change on tablets in order to indicate who is exploring which location. Once a student has finished rating a location, a green checkmark appears on that option card next to his/her avatar as a sign of completion. On the menu bar, there are rating progress bars for each student and step-lists with the current step highlighted, to help students understand their progress and the ongoing task. The set of functionalities to support each of the behaviors is shown in figure 3.4(a).

Study

We conducted an experiment with four groups of high school students using Pickit in a learning activity in class. We analyzed students' interactions with digital devices using indicators extracted from the recorded videos and data logs, using our collaboration model and decision-making models available in the literature [Ratcliffe, 1997; Hornecker et al., 2008; Rogat and Linnenbrink-Garcia, 2011]. The goal of the analysis was to give qualitative insights on how students behaved and collaborated in MSE. We tried to understand how the design of our application impacted activity and device usage, and contributed to the decision-making process. The results of the study are detailed in the paper [Tong et al., 2017a].

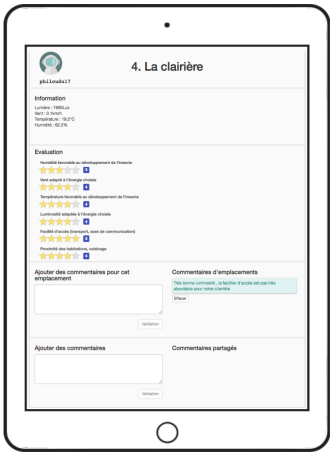
Collaborative behaviors analysis

Our study showed that the analytical process conducted during decision-making activities in the classroom can benefit from MSE properties. The combination of devices enabled tightly-coupled collaboration and loosely-coupled parallel work in the decision-making process, avoiding free-riding situations. The shared display seemed to increase students' awareness of the ongoing activity, and encouraged synchronous exploration of the same option by students, allowing a high level of freedom without interference. In this sense, the tablets improved independent exploration of options within groups. Students were able to develop their own judgments on the various options using criteria, thereby increasing their understanding. During discussions, the shared display supported students in synchronizing opinions and reaching a decision , while tablets served as supportive tools for debating when more information was needed.

From an educational point of view, according to teachers, students succeeded in making reasonable decisions and providing justifications to support their decisions. Students learned to argue and better structure a decision-making activity. Teachers also emphasized the positive effects of the application on students' soft skills. They were more inclined to collaborate with others even though they usually had great difficulties listening to and considering others' opinions. Former studies have demonstrated that prior friendship had a significant, large negative impact on group performance [Maldonado et al., 2009]. Our findings suggest that MSE may address this issue since using Pickit allows students to collaborate better than in a classic classroom situation.

Behaviors	Functionalities
Exploring (tabletop)	- Information button to show the decision making context (energy and insect) - Map to show the geographical condition of locations
Exploring (tablet)	- Showing data of locations - Rating tool based on criteria provided - Writing comments and arguments
Discussing (tabletop)	- Sharing everyone's comments - Providing average of the group's rating result - Showing location cards for comparison
Awareness & Regulation (tabletop)	- Showing who is exploring what - Progress bars for the rating processes - Check marker for the location that has been rated - List of steps in the menu bar

(a)



(b)



(c)

Figure 3.4.: Description of Pickit prototype developed in Tong et al. [2017a]: (a) Functionalities to support collaborative decision-making behaviors; (b) Tabletop design; (c) One student's tablet, from the top to bottom showing the location title, location information, rating, comment for the location, and comment in general.

3.3.2. Impact of devices form factor and configuration on collaboration

A part of MSE research focuses on the form factor and set-up of surfaces. As previous work on single devices showed that horizontal displays offer better opportunities for equal interactions and distributed work coordination among participants [Rogers and Lindley, 2004], we wanted to explore whether these findings also apply to MSE. Thus, to better inform the choice of MSE set-up configuration, we conducted a study on how the orientation (horizontal or vertical) of a large shared surface used alongside tablets impacts collaboration [Tong et al., 2017b].

Study

We adapted Pickit to implement a trip planning activity, comparable to that used by Rogers and Lindley [2004]. The task consisted of planning a trip itinerary to New York with a limited budget , requiring participants to agree on different choices such as the number of days, hotel, and activities to do. Such an activity is open-ended enough to enable various types of group organization.

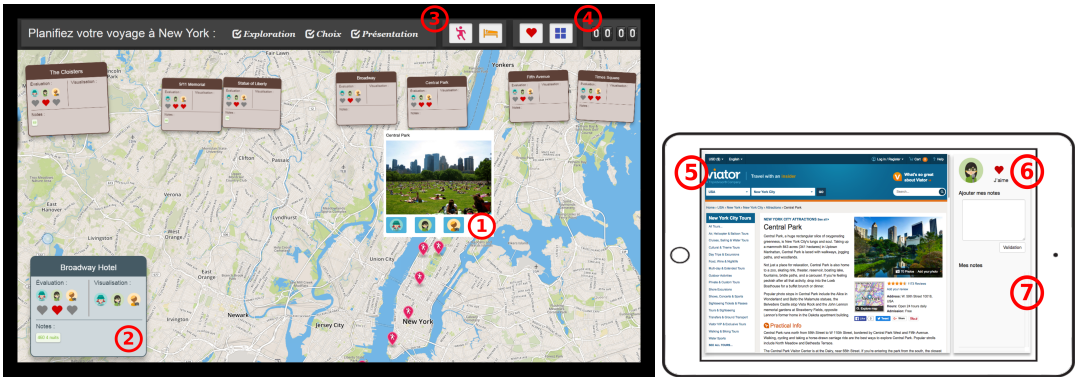


Figure 3.5.: Adaptation of Pickit for the trip planning activity developed in Tong et al. [2017b]. Top: shared surface showing the map + favorite locations. Bottom: tablets content with details on an attraction.

The shared screen displayed a map with markers for 15 tourist attractions and 8 hotels (Figure 3.5). Participants could push detailed information on their tablet (⑤) by tapping their avatar on a marker (①). Using their tablets, participants could individually add locations to their favorites (⑥) and take notes (⑦). A card per location showed its favorites and notes on the shared screen (②). Four filter buttons on the shared screen were used to show/hide attractions, hotels, favorite locations, and location cards (③). A timer in the top right corner reminded participants how much time was left (④).

We chose a between-group design with the shared display orientation as an independent variable with two conditions: horizontal and vertical. In both conditions, participants were standing (Figure 3.6). Overall, we observed six groups of three participants in each condition, which is comparable to similar studies of collaborative work with tabletops [Hornecker et al., 2008; Zagermann et al., 2016]. We recruited 36 participants (24 males and 12 females) aged between 21 and 31 years old (mean = 26.1; SD = 3.28). All of them were students at our university. Participants within a group knew each other.

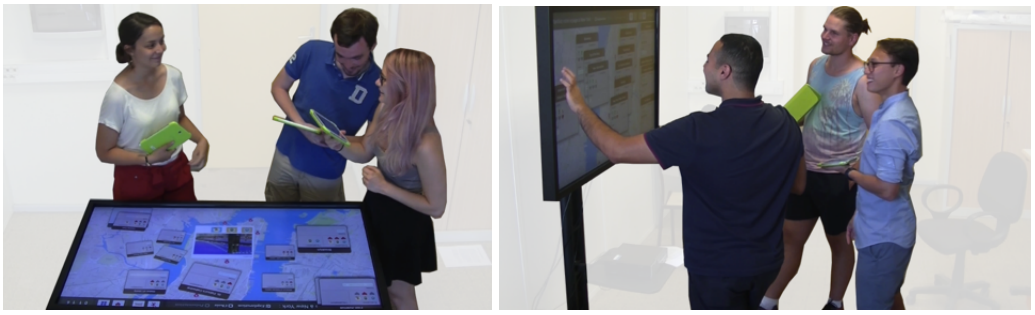


Figure 3.6.: Experimental set-up for the trip planning activity study described in Tong et al. [2017b] : a large interactive surface used alongside tablets. Left: the horizontal condition. Right: the vertical condition.

Collaborative behaviors analysis

We analyzed participants' behaviors at two different levels: low-level interaction and high-level group organization. We used both logs and video analysis to define a set of indicators as explained previously (Table 3.3).

Interaction: At a low level, we focused on how people interact with devices in MSE while conducting collaborative activities, especially when creating and interacting with content. We used log data to count touch events, how many notes participants submitted during the activity, and how many times they pressed the favorite button. We used video analysis to measure the number of touch events (tap, drag, or zoom) on UI elements of the shared display, to measure how active each participant was. Our analysis showed that large horizontal surfaces support more equality in physical interaction, whereas vertical surfaces lead to the emergence of a main interactor. In addition, combining tablets with a shared surface could reduce the differences between horizontal and vertical conditions, especially in the creation of and interaction with content, as highlighted in previous studies [Rogers and Lindley, 2004].

At a higher level, we analyzed activities related to group coordination according to the collaboration mechanisms defined previously.

Awareness: To analyze group awareness, we selected two positive indicators: reaction without explicit request and complementary action, which correspond to anticipation and assistance actions. We used two negative indicators of awareness: interference and verbal monitoring. Finally, we used verbal shadowing to measure and assess how participants maintained awareness [Hornecker et al., 2008]. Our analysis showed that groups maintained a good level of awareness in both conditions. However, in the vertical condition, this awareness came at a cost, as participants used far more verbal shadowing, i.e., announcing what they were doing. Moreover, they kept moving backward to observe the situation, before moving forward to analyze information on the shared display. In addition, there was little occurrence of implicit coordination. This could be attributed to the emergence of one main interactor handling the large surface. With horizontal displays, participants were more likely to spontaneously help other group members or finish the actions of others without verbal or explicit synchronization. Consequently, this could lead to more interference since participants interacted more with the horizontal surface.

Regulation: We analyzed regulation through the organization of the activity (group strategies, explicitly sharing labor, and roles taken by participants [Rogers and Lindley, 2004; Zagermann et al., 2016], planning and monitoring [Evans et al., 2016]) using videos but also logs (number of locations explored together and by each person). Our analysis showed that participants tended to use two different strategies in the two conditions. In the horizontal condition, groups explored the locations together and checked more locations, while in the vertical condition, participants distributed labor and each person explored fewer locations. In the end, the task duration was similar in both conditions. One strategy was not necessarily more efficient than the other.

Discussion and information sharing: To analyze participants' discussions, we marked in video each time participants talked about locations, budget, or itinerary. To analyze how participants used their tablets during discussions and how information was shared among the group, we captured each time they shared their tablets with others. We analyzed both verbal cues and participants' formations. We did not find a significant difference between the two conditions in the number of discussions within groups. This invalidates our hypothesis that discussions would be better supported in the horizontal condition. In both conditions, participants used tablets for sharing information or individually exploring information, to bring arguments into the discussion. Furthermore, unlike in previous work [AlTarawneh et al., 2015], we observed participants rearranging their formation, and forming more triad formations in the vertical condition.

3.3.3. Impact of reflexive indicators visualisation on regulation

This study was conducted during the M2 of Valentin Lachand that I co-supervised with Aurélien Tabard and Jean-Charles Marty (LIRIS-SICAL) in collaboration with the startup BIIN, as part of the EDUCATOUCH project supported by BIIN, ERASME, and the CANOPÉ network. In this study, we investigated the impact of different visualizations of indicators on regulation mechanisms using a tabletop. We studied two kinds of indicators: indexical indicators built into the objects being handled and symbolic indicators added to the activity interface. This work was published at IHM 2016 [Lachand et al., 2016].

Indicator visualization

The regulation of collaborative activities can be enhanced by providing feedback to users through the visualization of activity indicators. In this context, we were interested in designing dynamic indicators that remain visible throughout the activity. Specifically, we wanted to explore which type of indicator is better suited to support regulation.

We relied on the notion of semiotics introduced by Peirce, which allows us to characterize the relationship between an object and a sign (or visualization in our context) [Atkin, 2010]. We thus considered two visualization strategies based on Peirce's distinction between symbolic and indexical.

We refer to *symbolic indicators* as indicators whose visualization is presented in the form of graphs allowing for distinct visualization of numerical values (progress bars, pie charts, bar charts, etc.). The advantages of these indicators include ease of transposition from one activity to another (no strong integration, generality, rapid deployment) as well as the explainability of the provided information. However, we believe that these indicators can lead

to higher cognitive load and a shift in user attention focus [Benford and Fahlén, 1993]. The regulation process may then become less fluid, as it requires transitioning from the main activity to engage in meta-activity.

We refer to *indexical indicators* as indicators whose visualization is closely tied to the objects used in the activity. They provide information about the activity implicitly to users, while attempting to avoid interface overload and a loss of focus on the main activity. The potential advantages of these indicators include an unconscious interpretation leading to smoother regulation without cognitive back-and-forth between activity and regulation. However, the implicit nature of these indicators may potentially result in their underutilization by users who are unaware of their utility or unsure how to interpret them. Additionally, the strong relationship to the objects used in the activity may make them more difficult to transfer to other activities.

Study

Our study aimed to measure the impact of these strategies on collaboration regulation. We were interested in analyzing if the regulation process becomes smoother or more natural with certain types of visualization and if there was an impact on collaboration in terms of user participation rates.

We implemented a collaborative film classification task on a tabletop. The objective for the participants was to classify the films according to the criteria they consider most relevant. We defined several indicators for this activity, including the number of criteria created by each user, the number of links created by each user, the ratio of positive to negative votes for each user, progress towards a goal, etc. For each indicator, we associated an indexical visualization and a symbolic visualization as illustrated in Figure 3.7.

We conducted a preliminary study with 32 participants on the university campus (12 women, 20 men) divided into 8 groups of 4 users each. Four groups worked with indexical activity visualizations and four groups with symbolic visualizations. We collected interaction logs and used a questionnaire to gather their feelings regarding the activity (engagement, usefulness and information provided by the visualizations, the ease of understanding the visualizations, interest in reusing these visualizations in other activities).

Regulation analysis

The different visualizations did not play a role in standardizing participation rates. The results demonstrate uniform participation across all groups. Generally, regardless of the condition, participants always discussed each criterion orally before voting on it. In almost all groups (7 out of 8), one user validated the votes of all others after the discussion to progress more quickly. According to the regulation cycle of Järvelä and Hadwin [2013], we observed that users focused on the goal and developed a strategy to reach it as quickly as possible. Other regulation cycle mechanisms, such as perception, were not established, thereby limiting the utility of certain indicators.

The visualizations shaped collaboration strategies differently. Participants with indexical indicators used the color of the links (originally introduced to represent object ownership) to group objects thematically. This diversion of the indicator towards an action specific to

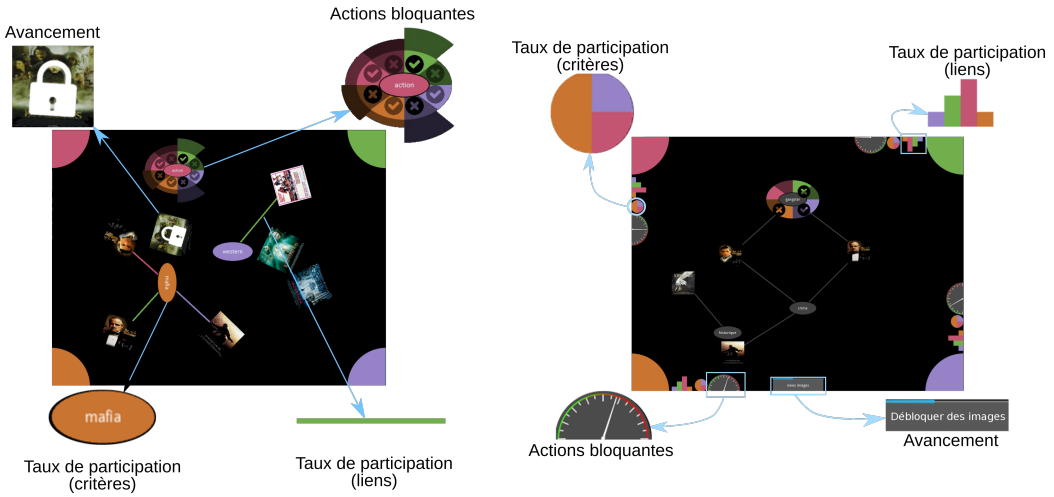


Figure 3.7.: Reflexive indicators visualization described in Lachand et al. [2016]. On the left : indexical indicators; On the right : symbolic indicators.

the main activity required more cognitive effort and consequently reduced the number of collaborative actions.

Finally, in terms of user experience, participants with indexical indicators had a better understanding of the indicators' meaning compared to those using symbolic indicators; however, it required more shifts of attention focus. Regarding the acceptance of indicators, overall, indexical visualizations were better accepted than symbolic ones, with greater confidence.

3.3.4. Summary of contribution

From a technical and design point of view, we developed several prototypes in which we investigated affordances for collaboration, in particular to support mechanisms identified previously: awareness, regulation, discussions, and information sharing. In particular, we explored the combination of a shared surface with mobile devices (tablets) to allow individual and collective activities suitable for discussions and information sharing. We proposed a set of indicators and features that increase awareness of what others are doing and facilitate regulation processes.

We conducted several studies either in ecological or laboratory settings to investigate the effects of these collaboration affordances on user behaviors. Thus, an important part of the contributions of this section is empirical. We demonstrated that the introduction of individual devices with a shared surface offers affordances well suited to support individual and collaborative reasoning and decision-making. This helped students to develop their own ideas and make free-riding more difficult. The social affordances provided by the MSE helped students to better listen to others' opinions, increasing social interactions in comparison to normal class settings according to teachers. In addition, the configuration of the environment, in particular the orientation of the shared surface, shaped group collaboration differently (equity and cohesion with a horizontal setting versus structured coordination and a main interactor in a vertical setting). Lastly, we demonstrated that the design of

UI features, such as the visualization of indicators related to the group activity, can have different impacts on regulation mechanisms.

3.4. Discussion

This chapter contributes to my first research axis which focuses on observing and understanding users' activities and experiences with technology to inform the design. I focused on environments dedicated to support collocated collaboration, and more specifically on multi-user surfaces and MSE in education. We developed several prototypes that allowed us to investigate the effects of affordances for collaboration on user behaviors. The different works presented in this chapter offer methodological, empirical, and technical/design contributions.

From a **methodological perspective**, we proposed models and methods to analyze collaboration. These tools contribute to the challenge identified in this chapter regarding the understanding of how technology shapes collaboration. We selected from existing literature four mechanisms that play an important role in collaboration (awareness, regulation, discussions, and information sharing). We demonstrated that these mechanisms were more easily observable than higher-level concepts such as coordination, cooperation, and communication. We listed the most commonly used indicators from previous works for each mechanism, mainly based on video analysis. We proposed to complement this approach using indicators extracted from interaction logs and a description of spatial arrangements and device use for each collaborative mechanism, relying on the F-formation framework. Even if the proposed method has demonstrated its potential to facilitate collaboration analysis, it could be significantly improved.

Firstly, the indicators extracted from the logs are not integrated in a generic way into our analysis grids. They were defined according to the needs of each study since they are usually dependent on the tasks and devices used during the activity. I believe that generic indicators for MSE should be defined for each of the four mechanisms identified in our model, drawing inspiration from a recent trend emerging in the domain of collaborative learning called collaboration analytics [Schneider et al., 2021]. This approach refers to computational methods for identifying salient aspects of collaboration from multiple group data sources [Martinez-Maldonado et al., 2021]. In particular, I believe that more automated and in-depth analysis of discussions could enrich the understanding of collaboration.

Secondly, interesting perspectives arise regarding the use of the F-formation framework to document spatial arrangement in collaborative environments. Throughout our analysis, we struggled to find a way to systematically code and represent micro-mobile behaviors and the transitions between F-formations. We only introduced mobile devices in our diagrams (as shown in Figure 3.3) as a first step in improving the notation of F-formation and mobility. We believe that progress is needed in the development of a visual language describing device use in F-formation, and in transitions between them. This would enable more systematic annotations and the ability to quantify formations more easily. Finding better ways to represent such dynamic behaviors would also help develop better models of collaboration and create better computational representations of the activity.

Finally, we only used an "objective" approach focusing on the analysis of behaviors (through analysis video or logs). From a multi-modal perspective, it would be interesting to include

subjective measures in our method, such as measuring user experience. For instance, Kreijns et al. [2007] proposed a scale to measure perceived sociability of computer-supported collaborative learning environments. The results of their exploratory study showed that the sociability scale has the potential to be useful as a measure for perceived sociability.

From a **design perspective**, we developed several prototypes to explore how to design affordances for collaboration. We explored different combinations and form factors of MSE mostly to support discussions and information sharing. Combining personal mobile devices with a shared surface supports both individual and collective activities, which are essential in collaborative learning, as underlined by Dillenbourg [1999]. We also explored different ways to visualize information on the shared surface to support awareness, regulation, and information sharing. To develop these elements, we relied on different concepts such as territoriality or semiotics. Mostly, the indicators were reflecting the group activity, enabling awareness or social regulation mechanisms.

We conducted several studies (either situated studies or lab experiments) to assess the impact of such affordances on collaborative behaviors, leading to **empirical contributions**. These studies allow us to better understand how technology shapes collaboration and demonstrate that different configurations and design choices (shared surface only, mobile devices, shared surface combined with personal devices) lead to different behaviors. From these observations, we derived **implications for the design of affordances** for collaboration, which I detail below.

As we emphasized previously, even if collaboration mechanisms can be analyzed as standalone behaviors, they should be considered as consequential behaviors when designing affordances. For instance, a good level of awareness makes regulation easier. Discussions can happen when one knows what the others are doing and when information is shared with others. Thus, in practice, designing affordances for collaboration should be considered as a whole, paying particular attention to **awareness**. We saw that the form factor of the shared surface or introducing personal devices could potentially produce awareness issues. We thus recommend incorporating awareness or change indicators on the shared surface or the handheld devices to help decrease the number of monitoring required. Shared indicators of group progress can also support **regulation**. To be effective, indicators for regulation should be based on a good analysis of the activity and the identification of sub-processes mobilized in regulation. It is important to ensure the intelligibility of the indicators, lest they become at best ineffective and at worst disruptive in the activity.

The introduction of several devices with a shared surface had consequences on the spatial arrangements of group members. This mobility, more or less strong depending on the configuration, shapes collaboration differently. In laboratory settings, tablet sharing led to changes in position, bringing freedom in group activities. Participants would have a personal workspace to conduct individual exploration and join group discussions when needed. We thus recommend that if the MSE is built for an activity involving discussion of rich content or data, cross-device interaction should support micro-mobile behaviors and support the exchange of complex information across devices. In highly mobile conditions, we also observed that complex information sharing should be better supported since it was challenging and frequently led to new group arrangements to cope with the lack of shared ground. Thus, there is a need for tools enabling collaborative interaction for *complex information sharing*. For instance, we could use proximity to enable information transfers between tablets, as proposed by Marquardt et al. [2012]. Depending on the arrangement of the group at a specific moment, we could also enable the duplication of screens for a

moment, or enable a focused/zoomed-in mode so that information is more readily visible to people.

To conclude, we proposed affordances for collaboration and examined how these affordances shaped user behaviors through the lens of four specific observable mechanisms. These contributions allow us to better understand the impact of technologies on user experience in multi-surface environments. The methodological aspects related to the analysis of collaboration can be applied in other environments, as I will demonstrate in the following chapters.

4. Analyzing User Experience and Behaviors to Understand the Impact of Technology Affordances in Immersive Learning Environments and Games

This chapter contributes to improve the understanding of users' activities and experiences with interactive systems and how technology affordances impact their behaviours and experience (Research Axis 1). I was particularly interested in assessing how design choices, considered as external factors, may influence the experiences of users in order to inform the design of such systems. In this chapter, I relied primarily on empirical approaches, conducting situated studies in the field of education in immersive environments and learning games. The contributions of this chapter thus are mainly empirical and lead to design recommendations and design tools (corresponding to my Research Axis 3).

4.1. Challenges of technology affordances on user experience in immersive environments and games for Learning

In the field of education and technology-enhanced learning, understanding how technologies can improve user experience and ultimately support learning, is an essential issue that is widely investigated. Usually technologies are considered for their ability to increase motivation and engagement, and are used to sustain specific aspects of learning according to their properties or affordances.

For instance, mobile devices offer great opportunities in the field of collaborative learning. They are especially interesting in their ability to provide digital information while still supporting social interactions between group members, which are essential elements of coordinated and shared activities [Tong et al., 2016]. More generally regarding collaborative activities, Kreijns et al. [2007] introduce social affordances as specific environmental characteristics that determine the sociability of a technology. They define sociability as *the extent to which a collaborative environment is perceived to be able to facilitate the emergence of a sound social space with attributes such as trust and belonging, a strong sense of community, and good working relationships.* The authors emphasize the importance of providing social functionality, as well as educational functionality, with users able to perceive the social patterns of activities, thereby making a complete learning experience [Kreijns et al., 2007].

In the field of VR and immersive environments, in the approach of considering immersion as a property of the system [Slater, 2003], the concept of affordance could refer to the "immersive potential" of a system defined by [Agrawal et al., 2020]. In their literature review, Oh et al. [2018] point out that immersion can be objectively measured by the technological

affordances of a system. They insist on the necessity to *understand how different technological features influence perceptions of social presence to inform the design of VR platforms*. In the same vein, Suh and Prophet [2018] proposed a framework to consider factors associated with immersive technology, distinguishing three different levels of stimuli (sensory, perceptual, and content-based). In their literature review, they note that flow theory [Czikszentmihalyi, 1990] is the most frequently used framework to assess the extent to which a user experiences a sense of immersion while using a technology. They also underline the lack of empirical research that explains systematically how and why these technologies impact user experience and performance. Regarding learning, VR environments allow users to experience higher feelings of presence and embodiment thanks to their sensory immersion which can benefit procedural and implicit learning approaches [Slater, 2017; Roussou and Slater, 2020]. These environments are often combined with approaches that promote cognitive immersion, such as role-playing [Checa and Bustillo, 2020] to promote active learning and engagement. In their literature review, Suh and Prophet [2018] showed that immersive technologies could trigger cognitive and affective reactions (such as flow, presence, and immersion), influencing positively learning effectiveness and engagement.

Lastly, some environments explore the augmentation of immersive environments with physical interactions. By combining physical and digital worlds, mixed-reality technologies can offer interesting affordances for learning games. In particular, they can offer more realistic and authentic experiences since they allow the reproduction of specific situations in which learners can be immersed [González et al., 2013]. In these situations, the authenticity of interactions is ensured by the combination of information related to the real environment and information provided by the digital simulation.

Research in immersive environments and learning games generally takes into consideration affordances by measuring the immersion, engagement, flow, or motivation perceived by learners. Some studies underline the importance of considering the levels of immersion, presence, interactivity, and fidelity for the artifact to be effective [De Freitas et al., 2010]. At the same time, some studies underline the lack of robust evaluation methods and the lack of diversity of factors considered in the evaluation [Checa and Bustillo, 2020; Suh and Prophet, 2018; Oh et al., 2018]. They argue that key factors directly related to the user experience should be considered to assure the success of games and immersive learning environments. This lack of empirical evidence on how technologies impact users' behaviors and experience is often highlighted, whatever the technology or type of environment used.

*The different works in various domains insist on the lack of **empirical evidence** to understand deeply the impact of technology on user experience.*

Moreover, the concept of affordance can be challenging to implement, regardless of the type of affordance considered. It is often difficult to bridge the gap between theory and practice. Designers lack practical elements based on empirical evidence to guide design choices [McGrenere and Ho, 2000]. To specify relevant affordances, choices can be made at different levels. The device itself or the interaction paradigm chosen may offer specific affordances. For instance, mixed-reality interactions can offer affordances related to object manipulation, whereas mobile devices may support context-aware interactions or even social interactions. Choices can also relate to the functionalities or features provided to users, or to the representation of information (in terms of graphical design considerations). For instance, in immersive environments, the field of view or the user perspective can influence user experience [Cummings and Bailenson, 2016]. In game research, [Tondello et al., 2019a] studied how people interact with games and are more or less motivated by the diverse game mechanics they experience. As another example, Kreijns et al. [2007] intended to

operationalize the different aspects of sociability into a Sociability Scale so that designers can take into account the different aspects of sociability in their design. While some items seem easy to transpose into functionalities (for example *"This CSCL environment enables me to easily contact my team mates"*), others seem much more difficult (for example *"I do not feel lonely in this CSCL environment"*), leading to different design possibilities and different impacts.

Thus a key issue is to improve our ***understanding of how technology and its affordances impact UX*** *to inform the design of such systems. In particular, I am interested in comparing the effects of different design choices on users behaviors and experience to be able to provide some useful recommendations for the design of affordances.*

To tackle this challenge, I conducted several situated studies to investigate how technology affordances influence the experience of users. In particular, I am interested in assessing how design choices corresponding to these affordances may impact user experiences and behaviors. I first studied the impact of interaction modalities (classical versus mixed-reality interactions) on motivation and engagement in a learning game (study presented in section 4.2). Secondly, I studied the influence of different scenarios and game mechanics in the same VR environment on flow perceived by users (study presented in section 4.3). Finally, I studied the influence of different user perspectives (first vs. third viewpoint) on the sense of social presence and collaboration in a collaborative serious game (study presented in section 4.4).

4.2. Impact of classical interactions versus immersive on motivation and engagement

This study was conducted during the PhD of Guillaume Loup I co-supervised with Sébastien George (LIUM - Université du Mans) and was funded by the ANR JENLab project. We developed a particular type of learning game for learning programming skills and investigated how technology allows learners to experience more authentic situations. In particular, we included in the game elements features that favor persistence and immersion, and we studied how these characteristics impact learners' motivation and engagement. This work was done in collaboration with Sébastien Iksal (LIUM - Université du Mans) and was published at the conference EC-TEL 2016 [Loup et al., 2016].

4.2.1. Designing for Immersion and Persistence

Digital Epistemic Games (DEG) are commonly defined as technology-enhanced and immersive role-playing games, where players learn to develop the capacity to deal with complex problems, involving multidisciplinary skills in authentic situations [Shaffer, 2006]. They also rely on important social interactions between learners, using the concept of communities of practice [Shaffer et al., 2009]. Unlike classical serious games, these games are anchored in the reality of the learning context. Mixed-reality technologies can offer more realistic interactions and allow the social, spatial, or temporal expansion of classical gameplay [Montola, 2005]. These technologies have been explored in augmented games, mixed reality games, and mobile computing games, which are also called pervasive games [Hinske et al., 2007]. Pervasive games can increase the number of stimuli by both a physical experience in reality

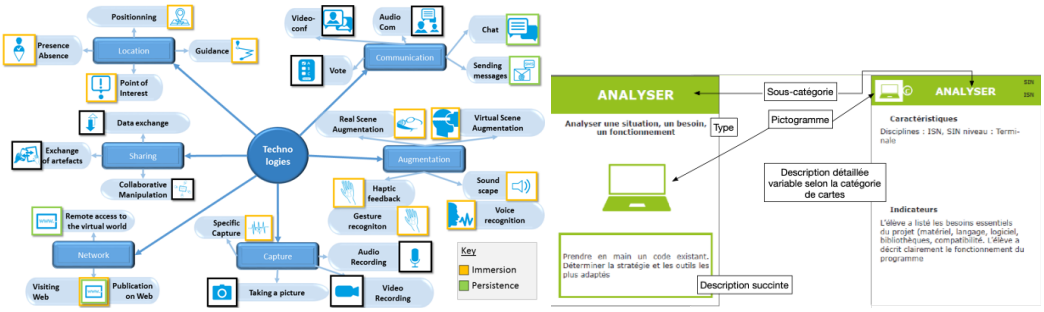


Figure 4.1.: JENCards used in [Loup et al., 2016]. Left side: Representation of all technological JENCards according to their categories of services. Orange boxed cards can be used for immersion and green ones for persistence. Right side: detail of the front and back of a card.

and a social and immersive experience in the digital environment. These games have opened up new perspectives in the field of education , and their effects on teaching and learning have been studied [Ardito et al., 2011].

We thus propose to extend the concept of DEG to Pervasive Digital Epistemic Games (PDEG), exploring two pervasive features: spatial expansion by *immersion* and temporal expansion by *persistence*. Immersion may be achieved using MR with many technologies such as screens, cameras, see-through glasses, mobile interfaces, and tactile or tangible interfaces. The objective is to digitally enrich a real situation or add realism to a virtual environment. Persistence can be achieved by having a persistent virtual world that continues to exist and evolve even when the player quits the game. This persistence affects how people interact with other participants by expanding the social dimension of a game. Instead of being the center of the world, one player becomes a member of a dynamic community [González et al., 2013].

We designed the game through several collective design sessions with game designers, researchers, pedagogical engineers, teachers, and students. During these sessions, we used JENCards [Serna et al., 2015], a set of physical cards that we developed during the project, as a support tool to establish a common language between participants and to help them explore the different characteristics of DEG, foster creativity, and integrate specific constraints and needs from the initial design phases. Our tool provides four categories of cards (skills, playfulness, social aspects, and technologies) which represent the main characteristics and affordances that should be considered in such games. Technological cards are represented as technological services divided into high-level categories, such as location or augmentation. Each card presents a particular service, such as positioning (for location category) or real scene augmentation (for augmentation category), illustrated with an icon and a brief description. To design for immersion and persistence, we classified the technological cards into three groups: immersion, persistence, and both (Fig 4.1).

4.2.2. Study

From a pedagogical point of view, the game mobilizes programming skills and knowledge of sustainable development principles. In the scenario, learners have to explore a planet by

programming a rover that collects data from the planet to choose the most relevant place to install a camp.

For experimental purposes, we developed two prototypes of the game: a prototype allowing only classical interactions using standard devices (DEG) and a prototype integrating persistent and immersive interactions (called PDEG). Immersion was added through several elements. The properties of the rover, such as its speed, were more realistic in the PDEG than in the DEG. Learners had a 3D view of the planet's terrain using Oculus Rift vision. The persistence of the world was represented by the exploration of the rover, which continued to collect data even when students were not playing (i.e., in-between classroom sessions).

The experiment was conducted in a high school in two classes of STI2D students, with 57 students aged between 16 to 18 years, the large majority of whom were boys (only 4 girls) . Each class attended 4 sessions of 2 hours. Two groups of 15 students played the DEG prototype (non-pervasive groups), and two other groups played the PDEG prototype (pervasive groups). After the final session, participants were asked to fill the Situational Motivation Scale (SIMS) questionnaire to measure their motivation [Guay et al., 2001]. We did not observe any significant differences in motivation types between the conditions (t-test performed) in intrinsic motivation (pervasive: M=4.11, SD=1.40 ; non-pervasive: M=4.70, SD=1.72), identified regulation (pervasive: M=3.06, SD=1.21 ; non-pervasive: M=3.32, SD=1.58), external regulation (pervasive: M=4.94, SD=1.51 ; non-pervasive: M=4.81, SD=1.52) or amotivation (pervasive: M=3.57, SD=0.98 ; non-pervasive: M=3.35, SD=1.15). We note that in both conditions , motivation was quite high after the game sessions, particularly regarding intrinsic motivation (pleasure and satisfaction) and external regulation (behavior regulated by reward).

4.2.3. Engaged behavior analysis

Using Bouvier et al. [2014b] approach, we considered three types of engaged behaviors in our analysis: environmental, self- and action-engaged behaviors. To measure each type, we defined indicators that we calculated for each group and each learning session using UTL [Iksal, 2011] to process logs.

Environmental engagement refers to the need for autonomy towards the environment that supports the activity. We used the indicator related to the time spent by learners on the consultation of information on the rover environment . This indicator was higher for learners in the pervasive condition. The results show that they were more likely to take different spatial and temporal aspects of information into account, combining different data sources offered by the environment (observation and logbook modules) in order to evaluate the rover progression.

Self-engaged behavior deals with the character or role adopted by someone during the activity and the way he/she contributes towards the group. The best indicator for this type of behavior in our game corresponds to the rate of land covered by sensors. This indicator demonstrated better results from learners in the pervasive groups (60.51% of coverage against 46.77% for the non-pervasive group) meaning that learners in the pervasive group were more engaged in collecting data to share with other players to find the best place.

Finally, action-directed engagement refers to the competence and autonomy needs regarding actions performed during the activity. In our game, most skills mobilized concern programming. Thus, we calculated indicators reflecting the programming method adopted by



Figure 4.2.: Indicators of programming methods adopted by learners (action-directed behavior) described in [Loup et al., 2016]. Left column : indicators for the pervasive group; Right column : indicators for the non pervasive group.

learners. We measured the number of simulations performed by learners before validating their program , the number of validations, and duration between two validations of rover programs (figure 4.2). The results clearly demonstrate that the pervasive groups wanted to ensure the validity of their program before submission (more simulations but fewer submissions), while the non-pervasive groups seem to have a "trial and error" approach (lots of submissions, fewer simulations).

4.2.4. Summary of contribution

From a design and technical point of view, we proposed to extend digital epistemic games (DEG) with pervasive features (immersion and persistence) to support more authentic interactions. We developed two prototypes of the game with classical and immersive interactions that we tested in real classroom settings. At a methodological level, we developed JENCards, a tool to support collaborative design sessions that allows exploring different affordances of such games.

From an empirical point of view, we demonstrated that the digital epistemic game, regardless of technological characteristics, motivates the students. Adding pervasive features to the game did not increase motivation in comparison to classical interactions. Regarding engagement, adding pervasive features shaped students' behaviors differently and improved the way they mobilized programming skills. We also observed that pervasive features, by improving immersion in the scenario, allowed students to be more engaged in their role and within their community, which is crucial in digital epistemic games.

This study thus demonstrates that the affordances of technologies can support learning outcomes by shaping users' behaviors to better mobilize skills through engaging realistic situations.

4.3. Impact of the type of scenarios on Flow

This study was conducted during the supervision of Sophie Villenave PFE with Élise Lavoué (LIRIS-SICAL) and Guillaume Lavoué (LIRIS-ORIGAMI), funded by the laboratory. In this study, we developed three scenarios in the same VR environment that rely on different game mechanics . We evaluated the influence of the scenarios and the time of practice in the VR environment on users' perceived flow.

This work was published in IEEE Transactions on Visualization and Computer Graphics (TVCG) and presented at IEEE VR 2024 [Lavoué et al., 2023].

4.3.1. Designing for Immersion and Flow

In their recent literature review, Suh and Prophet [2018] point out that many studies (such as [Bian et al., 2016; Hamari et al., 2016; Hassan et al., 2020]) rely on flow theory to investigate user experience in immersive technology research and to understand the impact of technology on user behavior . These studies measure users' psychological state as a cognitive response. In their study, the authors investigate the affordances that engage users in immersive environments and consider technology features as stimuli that arouse users' cognitive and affective reactions. They found that, beyond sensory and perceptual stimuli, the content of immersive technology can also impact user experience. This is in line with works that associate flow with user task characteristics, such as Shin [2018].

According to Suh and Prophet [2018], the impact of technology content is often investigated in immersive game research. In particular, they highlight that VR game content (such as competitive or collaborative games) can have different effects on users' cognitive involvement. For instance, Bachen et al. [2016] showed that flow increased users' motivation to play and Hamari et al. [2016] found a positive influence of flow on user engagement. Recently, Hassan et al. [2020] proposed a heuristic model of associations between preconditions of flow (challenge-skill balance, clear goals, sense of control, and unambiguous feedback) and all individual characteristics of flow (autotelic experience, concentration on task, transformation of time, loss of self-consciousness, and merging of action and awareness). Based on this model, they showed that preconditions induced experiences of flow, which in turn were associated with intentions to continue VR use and with longer VR sessions.

Regarding game design, Sweetser and Wyeth [2005] developed a GameFlow model to evaluate users' perception of flow and later Sweetser et al. [2012] enriched the model with a set of heuristics for designing and evaluating games. They propose general recommendations for each element of flow, which are quite high-level (for instance *"Players should feel viscerally involved in the game"* for Immersion). They also propose detailed heuristics which are very specific to certain types of games and which can be difficult to transpose directly into technological features (for instance *"The game elements should build up a rich and detailed world that is more like visiting a fully realized location than a constructed map"* for Immersion).

It therefore seems important to guide the design choices that will enhance the flow experienced by users, particularly in relation to the characteristics of the activity and the different tasks to be carried out in the environment. To tackle this challenge, we focused on varying the characteristics of an activity in the same VR environment to analyze their impact on the flow experienced. We chose to focus on different game scenarios, each based on a different genre (or mechanics), offering different tasks to complete.

4.3.2. Study

Our objective was to design a Virtual Environment (VE) rich enough and interactive enough to allow the creation of engaging and appealing game experiences. We chose to implement a single-storey house with five rooms and a terrace, with interactable objects. Based on this environment, we developed three game scenarios, each one integrating at least one commonly used game mechanics. The game design literature offers a wide variety of game elements or game mechanics, with different granularity levels and different approaches. Some empirical studies propose classifications that group together game mechanics [Heintz and Law, 2015; Tondello et al., 2017b]. To design our scenarios, we were interested in game mechanics that could be used in the same 3D environment and that would fit with VR scenarios (for instance moving in the environment or interacting with objects). Relying on these requirements, we selected the higher scoring mechanics that are common to both studies, namely action-adventure, role-playing, and exploration. We did not select social mechanics since we did not have the necessary infrastructure for the development of a multiplayer application.

Exploration scenario: For this scenario, players had no objective and were free to explore the environment without any goal. Three versions of the VE were implemented (the neutral one, a space version, and a post-apocalyptic version) . Players could successively visit the different versions.
Role-playing scenario: For this scenario, we specifically designed a story taking place in the virtual environment and unveiled it progressively to users during their experience.
Adventure scenario: We designed a scenario which combines adventure (finding 3 objects to build a bow) with some action components (zombie killing).

We recruited 48 participants (32 men, 14 women , 2 did not disclose their gender) , ranged from 18 to 31 years old , with the mean being 21.38 (SD = 2.2) years. Prior to the experiment, they filled out a questionnaire to collect information about demographics and average video game-play experience. Each participant experienced three VR sessions corresponding to the three game scenarios conducted in a given order selected among the six possibilities. Participants were assigned to one of the six possible orders to obtain a balanced number of participants for each possible order. Before starting the first scenario, participants were invited to practice previously learned controls in a specifically designed simple VE, allowing them to teleport and grab simple objects. Once they felt ready, participants were then teleported to the VE corresponding to the first scenario. At the end of each scenario (i.e., each session), participants removed their HMD and filled out the DFS-2 questionnaire on a computer to collect data about the perceived flow.

4.3.3. Flow analysis

We analyzed the influence of the scenario (*Exploration*, *Role-Playing*, *Adventure*) on users' perceived flow. Since our data were not normally distributed, we employed Friedman tests

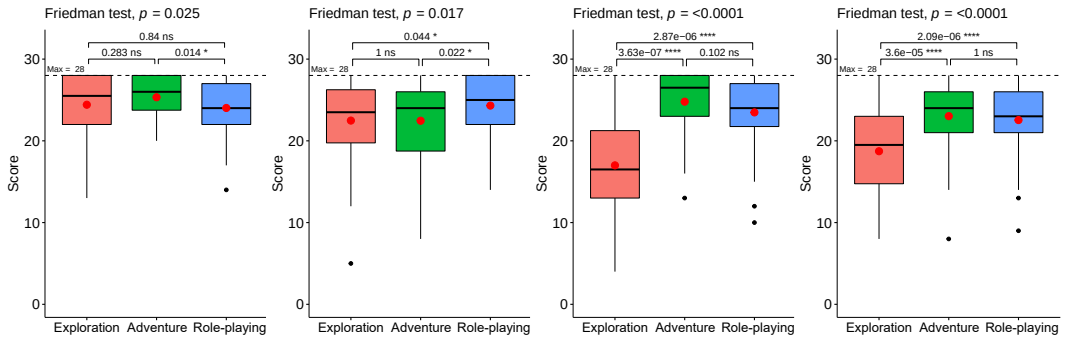
for each dimension of flow with the scenario as the independent variable. We subsequently completed this analysis by Wilcoxon post-hoc tests with Bonferroni correction for multiple comparisons.

Our results reveal that the three scenarios developed in the same VR environment have different impacts on users' flow experience, which are consistent with the design choices made in the scenarios.

On the one hand, Figures 4.3c and 4.3d show that the *Clear goals* and *Unambiguous feedback* flow dimensions have significantly lower scores for the *Exploration* scenario than for the other two scenarios. This means that participants had less precise objectives and considered the feedback of this scenario as less clearly defined than for the other two scenarios. We assume that this result can be explained by the design of the scenario since users had no specific tasks to complete, besides exploring the environment. In their study, Hassan et al. [2020] also underline that exploratory activities in VR have less defined clear goals but still allow the emergence of flow.

On the other hand, the *Role-Playing* scenario is the one for which users perceived a significantly higher *Action awareness* (see Figure 4.3b), meaning that they performed the actions rather "automatically". This result could be due to the story that guided users in the exploration of the environment, making the activity rather automatic.

These findings are in line with Shin [2018], who argues that the flow experience works independently from the technological quality and instead relies on the game mechanics and the actions users perform in the scenario.



(a) Autotelic Experience (b) Action Awareness (c) Clear Goals (d) Feedback

Figure 4.3.: Conditions for which significant effects of the type of scenario on user flow were found by Friedman tests. Results of Bonferroni-corrected Wilcoxon post-hoc tests (ns=not significant). Results published in [Lavoué et al., 2023]

Secondly, we showed that the impact of VR scenarios depends on the order in which they are performed, with several dimensions of the flow experience showing higher scores if the scenario was performed last, i.e., after the other two scenarios. All the figures and statistical analysis can be found in the paper.

Interestingly, the differences are mainly observed on the four dimensions that have been identified as preconditions to experience flow in recent work conducted by Hassan et al. [2020], who distinguish characteristics perceived in flow from preconditions for experiencing it. This means that the more familiar users are with the VR equipment and environment, the

more competent and in control they feel with their actions. They have clear goals and feedback and thus are able to perform rather automatically (referring to the increase in *Action awareness*).

4.3.4. Summary of contribution

From an empirical perspective, our results show that the characteristics of the activity (type of scenario and tasks completed in the environment) have an impact on specific dimensions of flow and that these effects depend on the order they are performed with the flow perceived becoming stronger when performed last. We demonstrated that the specific dimensions of flow that were directly influenced by the type of scenario corresponded to the preconditions of flow defined by [Hassan et al., 2020]. This means that the affordances offered by the immersive scenario can directly influence the time of practice required to enter a flow state. Thus, these results underline the importance of design choices, which can lead to different flow experiences.

This is in line with Hassan et al. [2020], who show that the intention to continue using VR is associated with the flow experience and argue that the more we understand the preconditions of flow in VR, the better VR environments can be designed to induce flow and immersive experiences.

4.4. Impact of different user perspectives on social presence

This study was conducted during the PhD of Anthony Basille, which I am co-supervising with Élise Lavoué (LIRIS-SICAL) and funded by the BODEGA project (Labex ASLAN). In this project, we used a collaborative serious game dedicated to soft skills measurement and training developed by Skilder, the industrial partner of the project. In this particular study, we explored how design choices and affordances of a virtual environment, such as the viewpoint (either first or third person perspective), impact UX and learners' behaviors. We analyzed the collaborative processes that emerge from learners' interactions and the sense of social presence. This work was published at the CSEDU 2022 [Basille et al., 2022] conference.

4.4.1. Designing for Presence

Soft skills, including collaboration and communication, are among the most important skills for success in modern society, and some works are investigating how to support their development through the use of serious games [Romero et al., 2015]. Serious games can easily immerse learners into a specific scenario, using role-playing methods, which allows learners to experience a specific situation with others (humans or artificial agents), learning about social roles and interactions [Marocco et al., 2015]. To be effective such games should consider the levels of immersion, presence, or interactivity [De Freitas et al., 2010]. We conducted a literature review on the study of presence in serious games. We found that presence was mainly investigated at an individual level, with potential positive results on motivation, user experience, and skill and knowledge acquisition. However, we also underlined that very few studies focused on collaborative serious games, creating a lack of empirical evidence on the

effects of social presence. Thus, in this study, we focus on investigating the social presence perceived by learners and the collaborative processes that emerge in such environments.

Studies focusing on social presence have shown that it has an impact on several factors of collaboration, for example increasing participation and interaction [Zhao et al., 2014]. In their meta-analysis, Richardson et al. [2017] show a strong positive relationship between social presence and students' satisfaction and perceived learning. As highlighted by Kreijns et al. [2007], social affordances of a technology should enable satisfying conditions for the emergence of social interactions. We believe that the impact of these affordances could be analyzed through the perceived social presence and users' behaviors. We are thus particularly interested in investigating if design choices regarding social affordances influence the sense of social presence and collaborative processes.

Regarding affordances, research investigates the relationship between the immersive quality of the environment and the level of presence experienced [Cummings and Bailenson, 2016]. Some works have investigated the impact of user perspective in virtual environments with contradictory results and different conclusions. Some studies show that the first-person point of view is the most appropriate condition to induce a high sense of embodiment, referring to the self-presence concept [Slater et al., 2010; Gorisse et al., 2017], while other studies did not observe any significant difference [Debarba et al., 2015] or a better perception of the avatar within its environment in the third-person point of view [Denisova and Cairns, 2015]. The study of Gorisse et al. [2017] also show that the user perspective has different impacts on users' performances and behaviors: the first-person viewpoint enables more accurate interactions, while the third-person viewpoint increases awareness in the virtual space.

Thus, little is known about the impact of the viewpoint on social presence and collaboration. This study tries to fill these gaps by investigating the influence of the user perspective (first versus third-person viewpoint) in the same virtual environment on social presence and collaborative behaviors.

4.4.2. Study

We used a collaborative serious game, designed to measure and train soft skills. The game relies on the collaboration between three players whose objective is to repair the four breakdowns of a submarine. At each turn, the water level rises progressively. The game is lost when the water level reaches a certain point. The submarine must therefore be repaired before it is completely filled with water. To do this, each player in turn can perform several actions. Each player has one movement point and two bailing points per turn (to move, to scoop, or to repair a breakdown). To repair a breakdown, there must be at least two players in the room. In addition, each player has a specific power that allows them to perform a special action. Players are able to interact with each other at any time, via a video and audio feed.

For study purposes, we developed two versions of the game integrating different viewpoints. In the third-person perspective version, players share the same view of the submarine map and they all have the same information on water levels and remaining time. The actions are directly performed on the map at each turn. In the first-person perspective, when it is their turn to play, the player must perform the actions directly in the virtual room of the submarine. In this case, only the two other players, who keep the third-person perspective,

can have access to the information regarding the general water level, the submarine map, and the remaining time.

We recruited 30 participants via the university's mailing lists. Due to technical problems during the experiment, as well as the COVID-19 pandemic, we were able to use the data from only 18 participants. Groups G1, G2, and G3 were associated with condition 1PP (First-Person Perspective), and groups G4, G5, and G6 were associated with condition 3PP (Third-Person Perspective). The average age was 23.5 years (SD = 2.5) and there was an equal distribution of nine men and nine women.

We collected the screen and webcam recordings of each participant. After the experiment, students were asked to fill in the Networked Mind Social Presence Inventory (SPI, 34 items) [Biocca and Harms, 2003] which measures social presence. The questions focus on the dimensions of co-presence, psycho-behavioral accessibility, and perceived subjective symmetry (as defined in chapter 2).

4.4.3. Social presence analysis

We discuss the results for each dimension of social presence.

Co-presence: Our results show that co-presence is not significantly impacted by the viewpoint (1PP: mean = 5.60, SD = 0.717; 3PP: mean = 5.35, SD = 1.066). Co-presence is mainly based on the perception of others using automatic classification of others' representation. Accordingly, this result can be explained by the fact that the virtual representation of the other players in the game is the same regardless of the viewpoint (webcam and voice). The perception of the other players' body thus does not change. This would certainly have been different with additional representations such as shadows or avatars when the two players are in the same room, as underlined by Kim et al. [2013], who showed that seeing their partner's avatar increased co-presence.

Psychobehavioral Accessibility: The results concerning psychobehavioral accessibility reveal a significant impact of the 1PP (M = 6.07; SD = 0.357), which seems to allow for greater psychobehavioral accessibility than the 3PP (M = 5.23; SD = 1.008). This difference could be explained by the asymmetry of knowledge introduced by the first-person viewpoint for several reasons. First, the lack of contextual information when players are in the first-person view may have forced them to communicate with the other two players in order to make relevant decisions early in the game, contrary to the third-person viewpoint. Second, players in the first-person view were more dependent on others, which led them to trust others more. Third, having access to others' perception of things is directly associated with "mind reading" (emotional states, for instance) and may reduce uncertainty in relationships [Planalp and Honeycutt, 1985].

Perceived subjective symmetry: The results regarding subjective symmetry reveal that participants in the 1PP condition have a better perception of what the others think of them than those in the 3PP condition. The mean of the correlation coefficients is larger in the first person for both co-presence (1PP: ρ = 0.876; 3PP: ρ = 0.707) and perceived psychobehavioral accessibility (1PP: ρ = 0.839; 3PP: ρ = 0.671). In other words, participants in the first-person perspective (1PP) condition perceived some sort of psychological and behavioral match between themselves and the other players. We may suppose that in the third-person perspective (3PP), some players felt they were giving more (i.e., attention) than the others

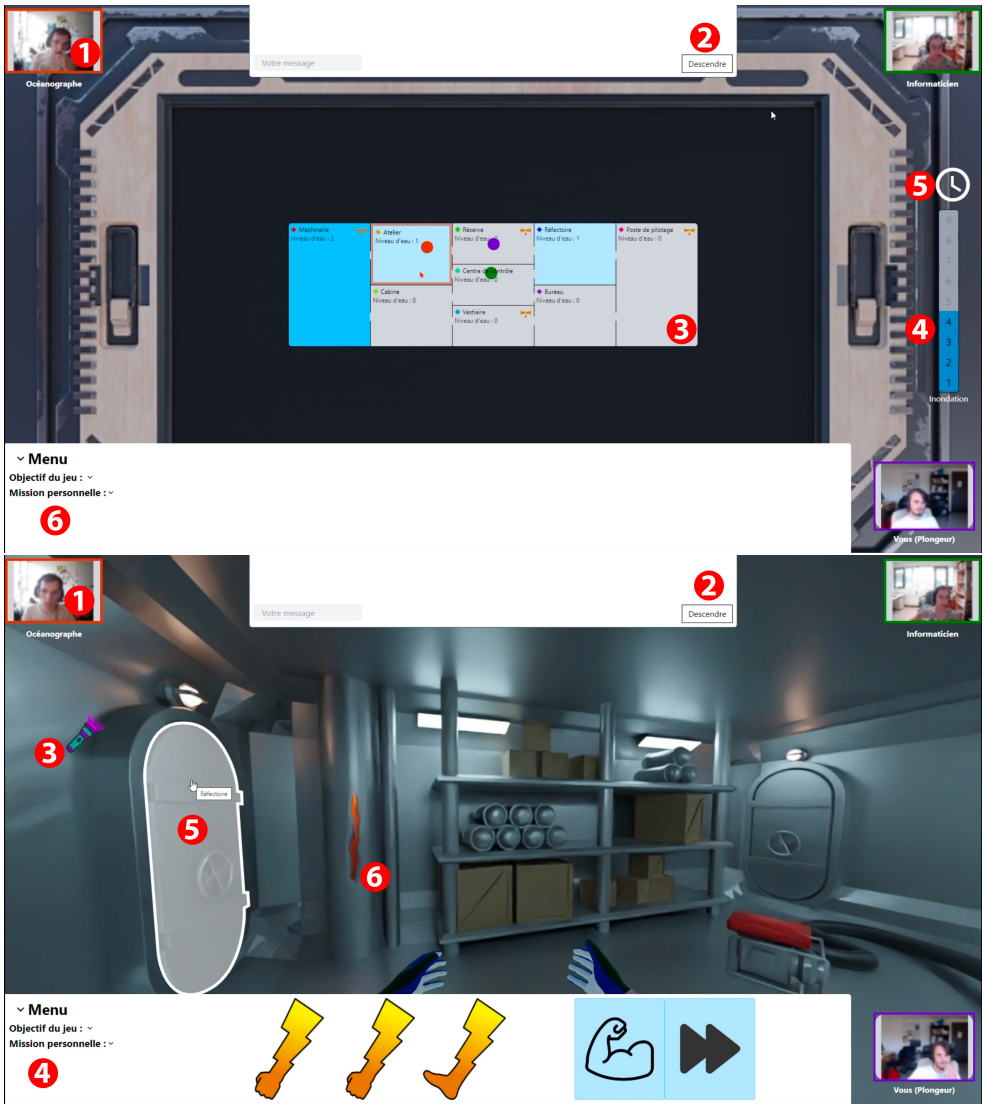


Figure 4.4.: Game Interface in [Basille et al., 2022]. Top: Third-Person perspective with the submarine map(3), the general level of water (4) and the remaining time (5). Bottom: First-Person perspective with the different actions possible (5 and 6) and the personal menu with special powers (4).

gave them. A certain imbalance could have been perceived because there was less cooperation since the three players had all the information. This assumption was confirmed during the interviews.

4.4.4. Collaborative behaviors analysis

To analyze collaborative behaviors in the game, we used our previous model defined in [Tong, 2017] (detailed in Chapter 3, Section 3.2), which identifies four mechanisms involved in collaboration: awareness, regulation, information sharing, and discussion. We defined a coding scheme for the video analysis to categorize participants' behaviors into the four mentioned processes (inspired by [Tong, 2017]). For each game, we counted the number of utterances in each category for each participant and for each group (sum of the utterances of the two games and the three players).

We observed a significant difference in the viewpoint on information sharing, which was greater in the first-person perspective (1PP) (M = 4.20; SD = 1.652) than in the third-person perspective (3PP) (M = 1.20; SD = 0.916). This result can be explained by the affordances of the environment, since some information (map of the submarine, general level of water) was not visible for players in the first-person perspective. Players had to compensate for this lack, communicating the missing information. We believe that this increase in information sharing contributed to the increase in sense of social presence, as explained previously for psychobehavioral accessibility. The increase in information sharing through the first-person view can really benefit learning. Indeed, according to Chi [2009], the co-construction of knowledge enhances understanding by allowing one to argue one's propositions, ask and answer questions, and open up new perspectives and reasoning. Winne et al. [2010] also support this assumption, arguing that information not accessible to others may require more collaboration to become knowledge shared by the group.

On the contrary, we did not observe any significant differences in terms of awareness, regulation, and discussion between the different viewpoints. These results may seem a little surprising, especially for awareness since we expected lower awareness with the introduction of asymmetric knowledge and more regulation to compensate. We therefore think that the higher level of information sharing compensated for the lack of awareness, but further studies will be needed to investigate more deeply the relationship between the four collaborative processes.

4.4.5. Summary of contribution

The main empirical contribution of this study is related to the impact of the virtual environment affordances induced by different user perspectives on social presence and collaborative processes. Our results show that the viewpoint has an impact on social presence in the collaborative game, and more specifically on the dimensions of psycho-behavioral accessibility and perceived symmetry. It seems that this is mainly induced by the knowledge asymmetry due to the affordances of the environment that differ in each view. This complements the work of Slater et al. [2010] and Gorisse et al. [2017], which show that the first-person view could increase the sense of self-presence measured through embodiment questionnaires. Regarding affordances, our results show that the affordances induced by the first-person perspective have a positive impact on social presence, with the asymmetry of knowledge creating a better relationship with others.

However, we did not observe a direct correlation between social presence and collaboration processes, except for information sharing. This could be explained by a quite high sense of social presence in both conditions and a low number of participants in this study. Further studies should be conducted since some works, such as Garrison et al. [2010], which show that social presence influences collaborative processes and develops learners' awareness of each other's existence, or Zhao et al. [2014], which show that "*an optimal level of social presence encouraged participation and positively shaped the dynamics of interaction, and thereby promoted collaboration*".

From these findings, we derived some recommendations for the design of collaborative immersive environments with social affordances, such as creating asymmetrical knowledge. These affordances of technology may induce a good level of social presence, strengthening the relationship among learners, suitable to support collaborative activities.

4.5. Discussion

This chapter contributes to my first research axis which focuses on observing and understanding users' activities and experiences with technology. I presented three different studies in the Education domain to investigate how technology and design choices may impact behaviors and experiences of learners. Even if the contributions are mainly empirical, along with some design contributions, some interesting methodological findings can be discussed.

From a **methodological perspective**, we adopted a classical comparative approach, developing two versions of a prototype (for Loup et al. [2016] and for Basille et al. [2022]) while varying an external factor (generally different design features or interactions). For the second study ([Lavoué et al., 2023]), we developed three scenarios implementing different game mechanics in the same virtual environment. To analyze the impact of the external factor, we took into consideration both subjective measures, using user questionnaires, and objective measures via logs and interaction traces. Questionnaires are chosen accordingly to the UX dimension considered (such as presence, flow, or motivation). Generally, our approach is driven by theories which offer frameworks for the analysis of behaviors at different levels of abstraction. We relied on frameworks already validated in previous work for analyzing behaviors, including Tong [2017] for collaboration and Bouvier et al. [2014b] for engagement. In these approaches, high-level behaviors are refined into observable behaviors thanks to indicators computed from interaction traces or from video coding.

From an **empirical perspective**, the three studies presented in this chapter contribute to a better understanding of the impact of technology and its affordances on user experiences and perception. Our studies demonstrate that design choices, offering different types of affordances in the environment, can shape user behaviors differently. In particular, we explored different types of affordances: motivational, epistemic, immersive, and social.

In Loup et al. [2016], our findings showed that the motivational affordances offered by the game itself (either extended with pervasive features or not) are sufficiently important to induce good motivation among learners. The extension with immersive and persistent features however influences learners' behaviors, in particular the way they mobilize specific skills and their cognitive immersion and involvement in their role. The interactions and design elements added in the pervasive game thus seem to foster the fundamental pillars of the epistemic approach, involving multidisciplinary skills in authentic situations and relying

on communities of practice, thus offering relevant **epistemic affordances**. In addition, as highlighted in different studies such as [Guay et al., 2001], our findings in Loup et al. [2016] show that intrinsic motivation and non–self-determined types of extrinsic motivation (i.e., external regulation) are not inversely correlated. This means that designing motivational affordances should be done considering all dimensions of motivation. We conducted several studies to investigate the impact of game elements on the different dimensions of motivation (presented in the following chapters).

Regarding **immersive affordances** of technology, we conducted two studies that investigated different design choices and their influence on flow and presence. In Lavoué et al. [2023], our results showed that the affordances offered by the game mechanics implemented in the three scenarios had different impacts on the flow perceived by users. In Basille et al. [2022], our results showed that the affordances induced by the first-person perspective had a positive impact on social presence and on information sharing, with asymmetry of knowledge creating a better relationship with others. We are currently conducting more studies in Anthony Basille's PhD to investigate deeper the potential correlations between social presence and collaboration. This preliminary study still shows that design choices can offer interesting **social affordances** to create relevant conditions to support socio-emotional processes associated with group dynamics (here the perception of the relationship with others). These aspects are fundamental according to Kreijns et al. [2003] for whom *"neglecting social psychological processes such as group forming, establishing group structures, and sustaining social relationships is considered as a pitfall"* for collaborative learning environments.

Finally, from a **design perspective**, contributions can be seen at two different levels. First, thanks to the adoption of theory-driven approaches, we can specify frameworks that inform the design of specific technological affordances. For example, extending the epistemic game concept with pervasive features in Loup et al. [2016]. This approach allows us to adopt a deductive posture, defining hypotheses or research questions related to the factors that we want to evaluate (particular technology, type of interaction, choice of interface elements) through the development of prototypes. Secondly, the empirical findings allow us to verify the hypothesis or explain aspects related to the research questions, and are then derived into design recommendations that reinforce the framework established previously.

To conclude, we examined how the epistemic, immersive, and social affordances of technology shape user behaviors and impact their experiences. For each study presented, we derived design recommendations to create supportive and engaging environments that will foster learning outcomes and meaningful experiences. In the next chapter, I present the contributions related to supporting the design of such environments.

5. Designing Motivational Affordances for Engaging Experience in Gamified Environments

In this chapter, I explore how to support the design of motivational affordances and their integration into technology to create positive, meaningful, and engaging experiences. My focus lies within the domain of education, particularly examining gamification as a form of motivational affordance. Adopting an empirical approach, we initially conducted a study to assess the impact of these affordances on motivation, which contributes to the understanding of how technology influences user experience (Research Axis 1). Subsequently, we proposed a design space for meaningful gamification that contributes to the development of design tools and methods (Research Axis 3). We used these tools to design a gamified platform named Ludimoodle, which allowed us to conduct several large-scale field studies in secondary schools.

5.1. Challenges in supporting the design of motivational affordances

In the field of education, several systematic literature reviews have demonstrated that gamified environments can benefit knowledge retention [Putz et al., 2020], students' performances [Briffa et al., 2020; Zainuddin et al., 2020a], and above all, learners' engagement and motivation [Zainuddin et al., 2020a; Subhash and Cudney, 2018; Dicheva et al., 2015]. However, several studies also found contradictory or mixed results, showing that users can be more or less receptive to different game elements [Orji et al., 2013; Monterrat et al., 2015, 2017; Mekler et al., 2017]. According to Sailer and Homner [2020], the results on motivational outcomes are not stable and depend on different factors. This highlights the challenges related to the design of successful gamification. Some authors investigate the integration of motivational affordances and meaningful gamification as strategies to tackle these challenges.

Motivational affordances refer to the properties of an object that can support users' motivational needs, thereby promoting their engagement and user experience. Building upon identified sources of motivation, primarily from SDT and flow theory, Zhang [2007] proposes a positive design theory for user well-being, emphasizing the importance of supporting autonomy, providing positive feedback, and inducing positive emotions during interaction. Deterding [2011] extends the concept with situated motivational affordances, referring to the well-known work of Dourish [2004] on embodied interaction. According to Deterding, the situation in which the user is situated plays an important role in motivational affordances: it offers its own motivating characteristics (situated affordances) in addition to influencing

the usage, meaning, and consequently the motivational affordances of the artifact in question (artifactual affordances). Situated motivational affordances, therefore, correspond to the opportunities to satisfy users' motivational needs created by the relationship between the artifact's characteristics and the capabilities of a user in a given situation. Taking into account the context and situation is crucial to ensure the success of the interaction and the satisfaction of motivational needs. In line with Deterding [2011], Sailer et al. [2017] argue that the impact of different game design elements should be evaluated within a given context and not as a generic construct. Lastly, Van Roy and Zaman [2019] underline that situational factors can distinctly shape the basic psychological needs — autonomy, competence, and relatedness — as outlined in SDT, consequently influencing motivation.

In the domain of gamification, the literature underlines the importance of considering the situation and the context when designing affordances of a technology and analyzing its effects on motivation.

Recent studies emphasize the importance of meaningfulness in the design process [Marache-Francisco and Brangier, 2013; Deterding, 2015; Nicholson, 2015]. Game elements should make sense to users, creating explicit connections to the given activity, and supporting feelings of competence, autonomy, and relatedness, identified as essential in the SDT. On the contrary, non-meaningful elements may be ignored or worse, may demotivate users [Nicholson, 2012; Deterding, 2015]. As highlighted by Sailer et al. [2017], the specific designs and realizations of gamification environments can take many forms and can combine game design elements in many different ways, often with arbitrary and subjective design decisions. In their study, they show that different game design elements can trigger different motivational outcomes. This lack of empirical evidence on how game elements impact users' motivation is often highlighted in systematic literature reviews [Dicheva et al., 2015; Sailer and Homner, 2020].

The literature underlines the need for empirical evidence 1) to better understand how motivational affordances implemented through game elements impact motivation and 2) to inform the design of meaningful gamification.

Even if gameful design methods have emerged recently from practitioners and researchers [Deterding, 2015; Tondello et al., 2016a], affording motivating and engaging experiences in non-game interactive systems remains challenging [Mora et al., 2017]. Many existing design frameworks provide only high-level guidelines and considerations to assist designers and no guidance on how to identify and fulfill user motivations. Lower-level design decisions, such as interface design patterns [Deterding et al., 2011], are poorly supported although they can also play an important role in improving user experience. [Marache-Francisco and Brangier, 2013] showed, for instance, that visual aspects of the gamified system play an important role in the perception of gamification.

Global design processes generally offer guidelines to consider the context and suggest the following steps: define the main objective, understand the user motivation, identify the game mechanics and analyze the effect of gamification [Werbach and Hunter, 2015; Kumar, 2013; Marache-Francisco and Brangier, 2013]. Deterding [2015] introduced more operational aspects with the concept of design lenses and skill atoms. However, these approaches offer poor guidance regarding customization and implementation of elements for a given context. To choose among elements, various lists of game mechanics are proposed [Tondello et al., 2017b,a]. However, the high number of elements in these lists makes their usage difficult in practical design sessions. Designers, developers, and other stakeholders, who may not have the same level of expertise regarding gamification, lack guidance on choosing among this huge number of elements considering their impact on motivation. As a result, they

are often limited to the use of only a subset of predefined well-known elements as pointed out by Tondello et al. [2017a], reducing creativity in the design process. To address this issue, some researchers are investigating the use of decision trees to guide decision-making [Marache-Francisco and Brangier, 2013] or design cards, such as [Ferro et al., 2014], which are traditionally used in design practice to foster creativity ensuring a common vocabulary and shared understanding among participants [Lucero et al., 2016; Peters and Calvo, 2021].

There is a need to overcome these limitations by guiding stakeholders during design sessions to support both high-level and lower-level decisions when designing meaningful gamification.

To address these challenges, we first explored how various design representations of motivational strategies (using different game elements) influenced motivation through a domain-independent study presented in section 5.2. Then we proposed a design space for meaningful gamification (presented in section 5.3) that we applied in various projects, mainly in the design of the Ludimoodle plateform (section 5.4).

5.2. Impact of the implementation of motivational strategies on motivation

This study was conducted during the PhD of Stuart Hallifax, co-supervised with Élise Lavoué (LIRIS-SICAL) and Jean-Charles Marty (LIRIS-SICAL), funded by the e-Fran Ludimoodle project, and in collaboration with Guillaume Lavoué (SICAL-ORIGAMI).

Facing the diversity of results when analyzing gamification impacts, we were interested in obtaining more generalizable findings on the main factors that have an effect on motivation. For this purpose, we conducted a crowdsourced study with 300 participants to identify the motivational impact of game elements by varying different factors. In this section, I present only the analysis of the effect of the design choices related to the implementation of motivational strategies (i.e., choice of game elements). The analysis of the impact of internal factors is presented in the next chapter 6, section 6.2. This work was published at the CHI-PLAY 2019 conference and received an honorable mention [Hallifax et al., 2019a].

5.2.1. Designing for Motivation

To broaden gamification design guidelines and recommendations, many studies have been conducted to measure the impact of game elements on user motivation. These studies are usually based on a small set of game elements in specific contexts and do not reach a consensus on their impact on user motivation [Seaborn and Fels, 2015a; Dicheva et al., 2015; Koivisto and Hamari, 2019; Sailer and Homner, 2020].

We believe that these heterogeneous results may be due in part to three reasons. First, the studies are generally carried out in different and particular domains (usually in health or education). This is in line with researchers arguing that gamification should be studied according to specific contexts [Sailer et al., 2017; Van Roy and Zaman, 2019], but this makes comparisons difficult. Second, they rely on specific and different user typologies or personality models. Third, they do not consider the same game elements or study different levels of abstraction, using consequently different vocabulary (”pervasive strategies,” ”motivational strategies,” ”game mechanics,” or ”game elements”). These studies either consider low-level

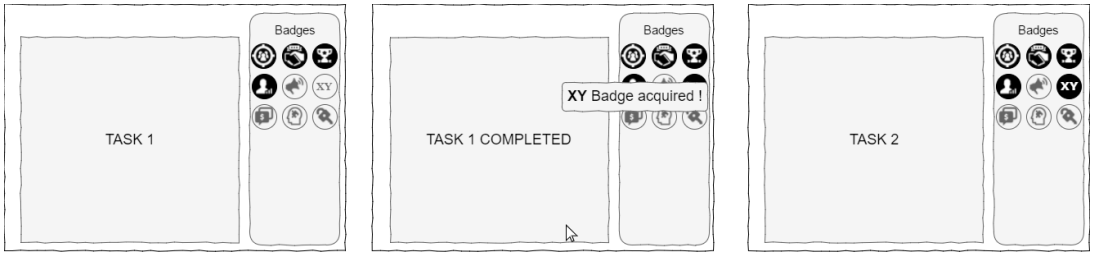


Figure 5.1.: An example of one of the 12 storyboards used in [Hallifax et al., 2019a]. They illustrate the game elements that implement the 5 motivational strategies. This particular one depicts the Badges game element related to the Rewards strategy.

game elements without considering the motivational strategies they support, or high-level strategies each represented by a single implementation.

The goal of this work was to obtain more generalizable findings on factors to consider to support gameful design choices for tailored gamification. For this purpose, we first proposed a clear distinction between the high-level motivational strategies and their implementation in the form of game elements. This concrete level allows comparison of different implementations of the same strategies. To do this, we reviewed the different works defining frameworks like Dynamics, Mechanics and Components (DMC) [Werbach and Hunter, 2015] which classifies game elements through three levels, from the most abstract to the most concrete elements. We then reviewed studies that evaluate the motivational impact of one or several commonly used game elements (focusing only on the "components" level of the DMC framework) and theoretical research that provides lists of game elements such as [Ferro et al., 2013; Huotari and Hamari, 2012; Kapp, 2012; Werbach and Hunter, 2015; Tondello et al., 2017a] or identifies links between game elements and the game mechanisms they support [Vassileva, 2012]. From this first list of game elements, we filtered to only include elements that were not directly linked to the content (such as storytelling) as they did not make sense for a non-specific user activity (as we wanted our study to be context-independent). We then grouped these game elements into an overarching motivational strategy they implement. As a result, we propose to consider 5 motivational strategies, implemented by 12 game elements listed in table 5.1.

5.2.2. Study

To investigate the influence of different factors on motivation, we decided to run a crowdsourced study independent of a specific context. To measure the interest of participants and their motivation regarding game elements, we asked them to rate different storyboards, a methodology inspired by Orji et al. [2017b, 2018, 2014]. The storyboards illustrate each game element independently of any specific user activity and domain (see an example in Figure 5.1).

To ensure that these context-independent storyboards would be understood by all participants, we ran a pre-study comparing them to similar storyboards for a math learning activity. We asked 8 participants to describe in their own words each storyboard and graded their understanding. We iterated on our storyboard design, validating the final design using

Strategy	Game element	Equivalent to
Rewards	Badges	Badges [Ferro et al., 2013; Jia et al., 2016] Rewards [Jia et al., 2016] Badges or Achievements [Marczewski, 2015; Tondello et al., 2016b]
	Points	Points [Ferro et al., 2013; Jia et al., 2016], Reward [Orji et al., 2017b, 2018, 2014], Points [Tondello et al., 2016b; Marczewski, 2015]
	Useful	Reward [Orji et al., 2017b, 2018, 2014]
Goals	External	Goal setting & Goal suggestion [Orji et al., 2017b, 2018]
	Self	Clear goals [Jia et al., 2016]
Time	Schedule	Reward Schedule [Ferro et al., 2013]
	Timer	Timer [Butler, 2014; Lavoué et al., 2018]
Social Interaction	Trading	Collection & trading [Marczewski, 2015; Tondello et al., 2016b]
	Teams	Cooperation [Orji et al., 2017b, 2018, 2014] Teamwork [Jeng and Teng, 2008] Guilds or Team [Marczewski, 2015; Tondello et al., 2016b]
	Discussion	Social network [Marczewski, 2015; Tondello et al., 2016b]
Progress	Compared	Leaderboards [Ferro et al., 2013; Jia et al., 2016; Lavoué et al., 2018] Competition and Comparison Orji et al. [2014] Comparison [Orji et al., 2017b, 2018] Social Comparison [Marczewski, 2015; Tondello et al., 2016b]
	Task	Bars [Ferro et al., 2013] Progress [Jia et al., 2016] Self-monitoring and suggestion [Orji et al., 2014] Self-monitoring and feedback [Orji et al., 2017b, 2018] Advancement [Jeng and Teng, 2008] Levels or progression [Marczewski, 2015; Tondello et al., 2016b]

Table 5.1.: The 12 game elements we used grouped by motivational strategy, and their equivalents in previous studies, described in [Hallifax et al., 2019a].

two additional participants. We found that the descriptions given for the context-free storyboards matched those given for the task-specific ones regardless of age or familiarity with video games.

The perceived motivational impact of each element was evaluated using a paired comparison protocol, which has been shown to be more reliable than direct rating [Pérez-Ortiz and Mantiuk, 2017]. Participants were shown pairs of storyboards and were asked to choose which one they estimated "*would motivate them more to use the system*" (forced-choice methodology). We opted for a *full* paired-comparison design, meaning that each participant evaluates *all possible* pairs of storyboards, i.e., $\binom{n}{2} = n(n-1)/2$ pairs with n the total number of storyboards. In our experiment, $n = 12$, leading to 66 comparisons. This full design, as opposed to incomplete ones, is more time-consuming for individual participants but allows a complete evaluation of participant agreement and consistency.

A total of 616 participants performed the whole task. As with all crowdsourced studies, certain measures are required to ensure that the responses given by participants are genuine. We employed two mechanisms to filter careless participants: (1) correct answers to four test questions where participants were expected to answer a certain way; and (2) individual consistency to evaluate the reliability of each participant. 180 participants were rejected according to (1) and 136 were rejected according to (2), giving a final set of 300 valid and consistent participants. This strict filtering ensured a high reliability of our results.

5.2.3. Perceived motivation analysis

To investigate if different implementations of the same motivational strategy resulted in different levels of perceived motivation, we analyzed the perceived motivation scores obtained for the game elements from the entire set of participants, as shown in Figure 5.2. Each participant provided a "vote" for a storyboard for each of the $\binom{n}{2}$ possible pairs ($n = 12$ in our case). Results per participant were recorded in an $n \times n$ preference matrix. As classically done with pairwise comparison experiments [Pérez-Ortiz and Mantiuk, 2017], we considered the number of votes received by each storyboard as its score of perceived motivational impact, which we normalized by the number of comparisons per storyboard. More details on how scores are computed from the preference matrix are provided in [Hallifax et al., 2019a].

For each motivational strategy, we performed pairwise paired t-tests on the score distributions to assess if significant differences existed between game elements. All the details about the statistical results are detailed in the paper.

Our results show that user motivation varies significantly with the different implementations of the same motivational strategy. We found significant differences for each strategy, particularly for the Reward and Time strategy. These differences are in line with other studies.

For instance, the *Rewards* strategy shows highly significant differences among the motivational impact of its implementations, with badges being the most positively perceived and points the least. Several other studies have also reported the efficacy of badge systems [Anderson et al., 2013; Denny, 2013; Grant and Betts, 2013], and Denny et al. [2018] demonstrated that their badge system was more effective than their points system.

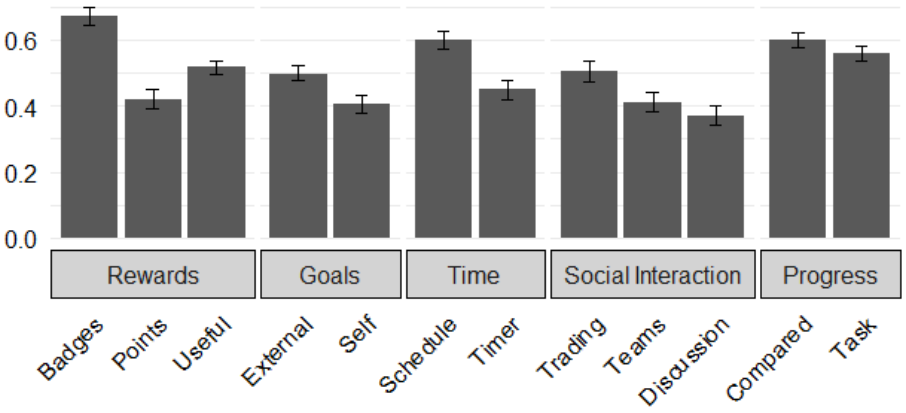


Figure 5.2.: Perceived motivational impact scores of all game elements, for the whole set of participants described in [Hallifax et al., 2019a]. The error bars show the 95% confidence intervals.

From a general perspective, the top four ranked game elements are badges, schedules, comparative progress, and task progress. This is in line with previous studies on social comparison [Hamari and Koivisto, 2013] and progress bars [Farzan and Brusilovsky, 2011]. From our comparison with domain-dependent studies, we found that badges and schedules can be used as motivating game elements for all users since they were two of the highest scoring game elements and had no negative influences in related studies. Designers can therefore feel confident that these game elements will have no adverse effects on user motivation.

Our results demonstrate that the implementations of a motivational strategy vary in their impact on user perceived motivation. This implies the need to be very careful when choosing the implementation of a motivational strategy during the design stages.

5.2.4. Summary of contribution

From a design point of view, we proposed to structure a list of game elements according to two different levels of abstraction, making a clear distinction between the high-level motivational strategies and their implementation in the form of game elements. This list was established after reviewing the related work in different domains with contributions of different types (theoretical research, empirical studies, design frameworks, etc.). We believe that this list can be a useful support for the design of tailored gamification, and we have integrated it into the design space described in the next section.

From an empirical point of view, we showed that the design choices related to the implementation of a motivational strategy into specific game elements can have different impacts on users' motivation. From these findings, we derived some design recommendations on the use of specific game elements. This study thus demonstrates that technology may motivate users differently according to the choices of motivational elements and their implementation.

5.3. Design Space for meaningful gamification

This work has been published in the Late-Breaking Works track of CHI 2018 [Hallifax et al., 2018], and a French version has been published in a longer paper for the STICEF journal [Lavoué and Serna, 2021]. In this paper, we present a design space for game element specifications which encapsulates nine design dimensions to consider in the design process. We also present a set of cards designed to facilitate the collaborative exploration of the design space during design workshops, and a board used to structure the design process.

5.3.1. Dimensions of the Design Space

Design spaces are traditionally used in HCI for identifying alternatives and structuring decisions in the design phase [Shaw, 2012]. We present a design space that encapsulates nine dimensions to consider regarding operational and visual aspects of elements for meaningful structural gamification. These dimensions serve to answer five questions that designers have to consider [Nicholson, 2012]: Why is the game element used? What is the focus of the game element? How does the game element work (content)? Who is concerned by the game element? and How is the game element represented (presentation)? Table 5.2 illustrates the dimensions and possible values.

Question	Dimension	Possible values
Why	Behaviour Change	Autonomy, Behaviour Encouragement / Discouragement, Performance
What	Granularity	Activity, Action, Operation
How (Content)	Strategy & Element	Rewards, Goals, Time, Self Representation, Social Interaction, Progress
Who	Actor	User, Group, Community
	Range	User, Group, Community
How (Presentation)	Visibility	Before, During, After, Always
	Style	Literal, Related
	Format	Relative, Absolute
	Precision	Precise, Fuzzy

Table 5.2.: Overview of the design space for meaningful gamification defined in [Hallifax et al., 2018].

Behaviour change (Why): Gamified systems aim to engage users in changing their behaviour or achieving their goals. This dimension helps designers reflect upon the design rationale behind the game element. We identified from the related works four behaviour changes according to designers' goals: Autonomy [Banfield and Wilkerson, 2014; Xi and Hamari, 2019], Behaviour Encouragement [Young, 2010; Denny, 2013], Behaviour Discouragement [Lehto and Oinas-Kukkonen, 2011], and Performance [Denny et al., 2018; Landers et al., 2017; Sanchez et al., 2020].

Granularity (What): According to the Activity Theory [Leontiev, 1978; Engeström et al., 1999], an activity is performed by a subject in response to a specific need or motive in order

to achieve an objective. By inciting designers to reflect on the granularity level, we lead them to question if the game element should address the main motive of the users (linked to the activity; i.e., running), their sub-goals (linked to actions; i.e., a 5km run), or conditions to perform the actions (linked to operations; i.e., stretching before running or breathing exercises).

Dynamic and Mechanic (How - Content): For meaningful gamification, designers have to decide which game dynamic and mechanic the game element should implement. Based on our classification (which derives from DMC [Werbach and Hunter, 2015] and on well-established game dynamics and mechanics), we list 6 commonly used game dynamics (Rewards, Goals, Time, Self-representation, Social Interaction, Progress), and classify some mechanics within each dynamic. As we focus only on structural gamification, we exclude elements such as Storytelling or Quests that are directly linked to the content.

Actor and Range (Who): These two dimensions refer to the actor who uses the element (actor) and who can see the game element (range): an individual user, a group of users, or a community. These design choices are crucial as they impact the type of regulation intended [Hadwin et al., 2011]. Individual users can self-regulate their activity individually or by comparison with others to achieve personal goals. Game elements shared by a group of users can help them co-regulate their own activities according to their own personal goals but also support shared regulation that requires interdependency and the complete cooperation of participants toward a common goal.

Visibility (How - Presentation): Schön [1983] assumed that reflection can occur both during the activity being performed (reflection-in-action) and after the activity, e.g., when mentally reconsidering it (reflection-on-action). The timing in which the game element is shown to the user can have an impact on the reflection process. We add a third value, "before," since we can also encourage users to establish goals and plan strategies.

Style (How - Presentation): Visual aspects of the gamified system play an important role in the perception of gamification by providing an appealing and immersive experience [Marache-Francisco and Brangier, 2013]. The Style dimension helps designers decide whether the game element should have a simple literal form (e.g., a basic progress bar) or one more related to the domain (e.g., a heart that fills up when you go to the gym to promote healthy living). Using domain-dependent metaphors can favor explicit connections with the given activity as recommended by Nicholson [2015]. However, the choice depends on users' intrinsic motivation for the domain and an independent style can reduce the risk of user amotivation.

Format (How - Presentation): Prensky [2005] pointed out that having a clear end state (i.e., a "win point") can increase performance. However, for some users "learning stops when goals are achieved" [Banfield and Wilkerson, 2014]. Therefore, we suggest presenting the game element in a relative (e.g., a score that shows four points out of a possible ten) or absolute format (e.g., a score that only shows four points) depending on the motivational context (users' profile or type of activity).

Precision (How - Presentation): Designers have to consider the precision of information presented in the game element. For some users, giving precise feedback on the activity performance can be motivating [Attali and Arieli-Attali, 2015]. However, for less competitive users, showing exact information can be demotivating [Orji et al., 2017b; Tondello et al., 2017a]. Thus, we suggest two possible values: precise (e.g., a leaderboard where the actor is shown to be 6th out of 14 users) and fuzzy (e.g., a leaderboard where the actor is shown as in the "Top Half" of users).



Figure 5.3.: Cards representing each dimension of the design space described in [Hallifax et al., 2018]. The colors represent the different questions to ask when designing gamification: green for why, blue for what, orange for who, red for how (regarding the content) and purple for how (regarding the game element presentation).

5.3.2. Tools to explore the design space

The design space presented above allows a systematic consideration of possible choices when designing game elements. This task may remain complex, especially if the different stakeholders involved in collaborative design sessions do not have the same expertise in gamification. To support the design process and to guide designers in the design space exploration, we created a set of design cards. Each card represents a particular dimension and contains the possible values, as well as examples, explanations of the choices and possible impacts on users' motivation (illustrated in Figure 5.3). The cards are designed to be used with a board structuring the different steps to perform during the definition of a game element. In addition to the properties defined by the design space, the board supports high-level decisions such as users and context considerations of the given activity (also identified in [Ferro et al., 2014; Marache-Francisco and Brangier, 2013]), and lower-level specifications such as visualisation (element mock-ups) and operational rules. We decided to integrate these aspects only on the board since they are closely linked to the domain to be gamified and would probably have too many forms or values to be represented by specific cards. These domain-dependent elements are thus instantiated during design sessions for each context and game element.

5.3.3. Summary of contribution

From a design point of view, this work aimed to develop a method and tools to support gamification design. We extended the concept of meaningful gamification to operational and visual aspects of game elements. To help designers with these complex considerations, we proposed a design space that can be used in a vast variety of contexts. The design

space is accompanied by a set of cards and a board to facilitate its collaborative exploration during the design process. We were able to test our tools during a workshop held with different stakeholders (described in the following section). In this workshop, we observed that participants rapidly took ownership of the design materials, sharing common ground on the gamification process and favouring communication. As the workshop progressed, participants were able to converge on design agreements faster. Discussions focused on both the impacts on students' motivation and fulfilling the different stakeholders' interests.

5.4. Ludimoodle gamified platform

We used our design space to develop a gamified environment in the Moodle learning management system named LudiMoodle, as part of the ANR LudiMoodle project.

All the learning content was created by the participating teachers so that it would be as close as possible to their teaching practices. The teachers designed eight lessons, composed of several quizzes (4 to 10) that covered the topic of secondary school level basic algebra (in particular literal arithmetic). The quizzes were designed as *training exercises* since teachers had observed that learners generally found these exercises to be boring or too repetitive, and they wanted to make these exercises more engaging for learners. Within a lesson, to successfully complete a quiz and progress to the next one, learners had to answer at least 70% of all questions correctly (otherwise they had to start the quiz again).

To gamify the learning platform, we used an iterative design process with participatory design sessions with the different stakeholders of the project (teachers, game designers, educational engineers, the company in charge of the development), using our design method.

First, following the same process as in Tondello and Nacke [2020], we ensured to select game elements that would appeal to different learners by covering the main game elements identified in the literature. The most frequently used game elements in studies in education are points, badges, and leaderboards [Subhash and Cudney, 2018; Zainuddin et al., 2020a], followed by avatars and progress bars or levels [Zainuddin et al., 2020a; Barata et al., 2017; Hallifax et al., 2023]. In their literature review on tailored gamification, Klock et al. [2020] list the most commonly used game elements, all fields considered, which are, in order, customisation (i.e. avatar), badges, challenge, level, competition, leaderboard, and points. We compared these common elements with the classification proposed in our design space to select game elements that would cover the different game dynamics. We selected points and badges (for the Reward dynamic), progress bar and ranking (corresponding to leaderboards and competition) (for the Progress dynamic), and avatar (for the Self representation dynamic). In addition, teachers selected timer (for Time pressure dynamic) for its suitability for the quiz format, although this element has been little studied in the literature [Butler, 2014; Monterrat et al., 2015]. We also ensured that each of the six game elements corresponds to at least one of the different Hexad player types [Marczewski, 2015] and cover the different kinds of learners' motivation as defined in the SDT [Deci and Ryan, 1985b, 2000].

The learners themselves were not directly involved in the design of the gamified platform. However, similar learners (same age and class level) who had interacted with previous prototypes of the platform participated in focus groups to refine the design and functionalities of the game elements.



Figure 5.4.: The LudiMoodle platform: example of a gamified quiz. The upper part shows the game element (here the avatar), while the lower part contains a quiz question.

Each of the game elements had a small information popup that opens at the start of each lesson to inform and remind learners how it worked. Learners could access this popup at anytime via a button on the interface. Figure 5.4 illustrates the gamified environment with the avatar game element. This game element showed a goblin-like character that learners could personalise with various clothes and equipment. As the learners progressed in a lesson, they could unlock a different set of objects to use (e.g. medieval, fairy tale, pirates). The avatar could be personalised via an inventory menu displayed near the top of the game element. In general, when learners achieved the required 70% in each quiz in a lesson, they could unlock 1 or 2 objects. The avatar matches the need for autonomy regarding the SDT [Sailer et al., 2017; Zainuddin et al., 2020a]. This kind of game element is generally recommended for Free Spirits, as it provides them with a personalised representation of themselves [Marczewski, 2015; Klock et al., 2020], and for Disruptors [Klock et al., 2020].

The details about the design rationale for each game element are available in Appendix A.

5.5. Discussion

From an **empirical perspective**, in Hallifax et al. [2019a] we demonstrated that the design choices related to the implementation of a motivational strategy into specific game elements can have different impacts on users' motivation; offering consequently different motivational affordances. Rewards are a good illustration of this since Badges are the highest-rated of any of the implementations, whereas Points are one of the lowest-rated ones. Therefore, designers should be guided when choosing and implementing a motivational strategy.

We also analyzed the influence of the context by comparing our results with domain-dependent studies. This allowed us to identify several game element recommendations that are independent of the context, in particular for badges and schedules. This choice to use context-independent scenarios to evaluate the motivational impact of game elements independently from a specific context may, however, have an influence on users' perceived motivation. Certain game elements may be less motivating for users when shown without a concrete task to carry out. We suppose this to be especially true for Useful Rewards or Progress Task. This suggests that there is still a need to collect empirical evidence to investigate deeply these influences.

From a **methodological perspective**, we used a different approach from the ones usually used in gamification studies, consisting of a crowd-sourced study using pairwise comparisons instead of using direct rating to measure the perceived impact of game elements on user motivation. Forced-choice paired comparison has been shown to be less cognitively demanding [Clark et al., 2018] and to provide higher accuracy [Shah et al., 2016] compared to Likert-type rating. We noticed an interesting effect of this protocol in comparison to other studies: it forced users to choose which game elements they prefer and we therefore obtained a ranking of game elements (meaning that a user could not vote all game elements as equally motivating). This type of approach can be interesting for tailored approaches where it is important to establish an order of preferences between different elements.

From a **design perspective**, we proposed a classification of the most commonly used game elements according to two different levels of abstraction, making a clear distinction between the high-level motivational strategies and their implementation in the form of game elements. This list was then integrated into the design space presented in Hallifax et al. [2018].

We believe that this classification could also serve the tailoring process or dynamic adaptation which I detail in chapter 7, for instance by changing a game element to another regarding its motivational strategies.

In order to provide designers with the tools to create meaningful and motivating game elements, we proposed a design space supporting the common high-level steps of gamification design while also encapsulating lower-level design decisions during the design process. We also proposed a set of design cards and a board that aim to support the design process for collaborative design sessions. We tested the method to design Ludimoodle game elements with teachers and game designers during one co-design session. Even though this first small trial was promising; more formal studies should be conducted in order to test the expressivity and efficiency of the tool. This need for more evaluation of tool efficacy has been underlined as a general opportunity for future research on tools for collaborative design ideation [Peters and Calvo, 2021].

Another area for improvement concerns fostering creativity and providing support for inspiration. As underlined by Halskov and Dalsgård [2006], sources of inspiration play an important role in the design process. With their inspiration cards, they demonstrated how this tool successfully framed and guided workshops with disparate participants and brought various sources of inspiration into the design process. In our observations, we saw that participants had difficulties using the "Behavior Change" dimension as they always selected the same behaviour. We could enrich our cards with examples of the different behavior changes possible and from a more general perspective with game elements inspiration boards.

In conclusion, we have demonstrated how, using an empirical approach, we have been able to better understand the impact of motivational affordances on user motivation and propose tools to guide the design of such affordances. In this chapter, I examined the external factors, such as design choices, that impact motivation. In the next chapter, I will explore the internal factors (i.e., user preferences and characteristics) that can influence motivation.

6. Modeling Users in Gamified Environments

This chapter addresses Research Axis 2, which is related to user modeling. The first objective is to identify the factors specific to users, such as preferences or characteristics, that influence UX. The second objective is to integrate these factors into user models. In this chapter, I describe the work conducted to meet these two objectives in the field of tailored gamification for education under the co-supervision of Stuart Hallifax, PhD, as part of the ANR Ludimoodle project. In this work, we focus on motivation and engagement, which are among the most important UX dimensions in the field of education.

6.1. Challenges in modeling users in gamification

Even if recent systematic literature reviews and meta-analyses on gamification are rather positive [Subhash and Cudney, 2018; Zainuddin et al., 2020a; Briffa et al., 2020], some reviews underline contradictory or mixed results regarding the effects of gamification. This could be explained by the use in all the reviewed studies of what is commonly referred to a "one size fits all" approach, i.e. providing learners with the same gamified experience. Recent research shows that learners have different expectations, preferences, and needs from the learning experience [Hassan et al., 2021; Kim and Lee, 2015]. This finding is echoed by van Roy and Zaman [2018] who concluded that "the effects are highly personal and can differ widely between different learners". These mixed results of gamification have also been observed in other domains [Koivisto and Hamari, 2019; Klock et al., 2020] and the majority of the meta-analyses cited above agree that the effects of gamification are highly dependent on specific contexts, which vary across individuals. Thus , researchers have begun investigating whether adapting game elements to individual learners (or users' characteristics, preferences, and motivations) could have a greater impact.

One direction of research is to identify the relationships between game elements and user characteristics (user profiles) to propose relevant game elements to users [Seaborn and Fels, 2015b], particularly in the field of education [Hallifax et al., 2019b; Oliveira et al., 2022b; Bennani et al., 2022]. Within user profiles, Oliveira et al. [2022b] distinguish students' traits, such as player (or gamer) profile, learning style, goal orientation, or personality trait; demographic factors such as age or gender; and psychological states such as motivational stage. Regardless of the field or studies, the player profile, which classifies users according to their game preferences, is the most used model. According to Klock et al. [2020], the player profile was studied by 45% of the works, followed by gender (14%) and personality traits (12%).

Regarding player profiles, the majority of the works rely on different well-recognized player typologies, such as BrainHex [Nacke et al., 2011, 2014] and Hexad [Marczewski, 2015]. The BrainHex player typology [Nacke et al., 2011] was originally developed specifically as a "gamer" typology, taking inspiration from neurobiological research [Bateman et al., 2011].

It proposes seven player types: Seeker, Survivor, Daredevil, Mastermind, Conqueror, Socialiser, and Achiever [Bateman et al., 2011]. Various studies in both game and gamification rely on this typology [Busch et al., 2016; Lavoué et al., 2018; Monterrat et al., 2017; Orji et al., 2017a, 2013, 2014]. Marczewski [2015] more recently developed the Gamification User Types Hexad framework specifically for gamification, accompanied by a measurement scale [Tondello et al., 2016b, 2019b]. This typology is based on Self Determination Theory [Ryan and Deci, 2000b]. The Hexad typology designates six different user types: Philanthropists, Socialisers, Free Spirits, Achievers, Players, and Disruptors. Several recent experimental studies have been conducted to identify the motivational impact of game elements according to Hexad user types [Mora et al., 2018; Orji et al., 2018] or propose personalization approaches [Knutas et al., 2018]. Finally, a few recent studies [Jia et al., 2016; Orji et al., 2017b; Denden et al., 2018, 2021] on tailored gamification consider "personality traits" to identify user preferences, mainly the Big Five Factors composed of five user types [Goldberg, 1992, 1990].

To measure the suitability of game elements for each user type, some research explored the use of direct ratings by experts [Lavoué et al., 2018]. In this case, experts were asked to rank which game elements would be most appropriate for each user type. Other works focus on users ' feedback using direct rating or standard questionnaires and scales, or behavioral metrics. For instance, Tondello et al. [2016b, 2017a] calculate the correlations between Hexad user types and various game elements directly rated by users using a Likert scale. Orji and Moffatt [2018] used a validated scale for assessing perceived persuasiveness. The recent meta-analyses on tailored gamification in education [Oliveira et al., 2022b; Bennani et al., 2021] show that the most common approaches use statistical techniques to highlight correlations between game elements and user types. However, the diversity of models makes it difficult to compare game elements' effects based on user characteristics. In addition, most of the studies on the impact of gamification on users only consider the dominant user type, i.e. the type that has the highest score [Gil et al., 2015; Lavoué et al., 2018; Ferro et al., 2013]. Studies considering personality traits take all types into account [Orji et al., 2017b] and a few recent studies also do this for player typologies [Orji et al., 2018] or establish hybrid profile clusters for finer-grained analysis [Mora et al., 2018]. These works generally rely on statistical approaches well-suited for complex relationships, such as Partial Least Squares Path Modeling (PLS-PM) [Hair Jr et al., 2016; Sarstedt et al., 2017], to study the influences of each type (or dimension) of a profile on specific metrics [Orji et al., 2014; Tondello et al., 2016b; Orji et al., 2017a; Tondello et al., 2018; Orji et al., 2018]. The metrics used can come from different sources of data, most of all from answers to user questionnaires and more rarely from behavioral metrics (task duration or grade for instance).

Thus, considering the diversity of user models, there is a need to better understand the relationships between game preferences and player typologies to support user modeling. In addition, in these statistical approaches, subjective measures based on questionnaires are mainly used as observed indicators. There is a challenge to investigate the use of more objective indicators, such as behavioral metrics related to engagement.

Finally, since learners have different motivations when using a learning environment [Vassileva, 2012; Hamari et al., 2014; Monterrat et al., 2017], only a few tailored approaches investigate how to better integrate these aspects into user models. For instance, Hassan et al. [2021] rely on students' learning styles identified by their interactions with the system to propose an adaptive gamification experience. Their study revealed that the motivation of learners increased by 25%. However, learners' profiles in this case do not include directly a representation of their motivation. Roosta et al. [2016] first proposed a user model based

on motivation. They conducted a study where they adapted game elements to learners' motivation types (participants were either motivated by Mastery approach, Performance Approach, Mastery Avoidance, or Performance Avoidance). Their study showed that participants whose game elements were tailored to their motivation type experienced a significant increase in motivation after using the system for one month, compared to learners who had randomly assigned game elements.

This approach is only in its early stages and there is a need to investigate more deeply ***how motivation should be integrated in user models****.*

Motivation is frequently studied through the lens of SDT in gamification research [Seaborn and Fels, 2015b; Zainuddin et al., 2020b; Tyack and Mekler, 2020], as presented in Chapter 2. The theoretical framework is essentially used to support the design of game elements or to assess the effects of gamification on motivation [Tyack and Mekler, 2020]. To our knowledge, no works propose to integrate the different types of motivation defined in the SDT into user profiles. In addition, most of the studies investigating the impact of gamification on motivation only consider motivation as a whole, or distinguish only two types of motivation (intrinsic versus extrinsic). They do not investigate the different fine-grain types of motivation offered by the continuum of self-determination in the SDT. There is thus a lack of empirical evidence to establish correlations between game elements and the different types of motivation, as done for player profiles. Only two studies have investigated the effect of gamification on different types of motivation [Buckley and Doyle, 2014; van Roy and Zaman, 2018]. In particular, the longitudinal study of van Roy and Zaman [2018] showed that all types of motivation changed over time, highlighting the need to consider the variation of motivation.

There is therefore a need for a better understanding of the effect of gamification on the different types of motivation and on their variation, to be able to integrate these empirical findings into user models, using for instance statistical approaches similar to the ones used for player profiles.

In conclusion, regardless of the adaptation process and user models used, the recent meta-analyses on tailored gamification report mixed results when adapting gamification to learners, underlining that most of the experiments do not provide sufficient statistical evidence and highlighting the need for more empirical studies [Klock et al., 2020; Oliveira et al., 2022b; Rodrigues et al., 2021b].

To summarize, the main challenge lies in investigating more deeply which ***learner characteristics*** *should be considered in the adaptation process* ***depending on the game element used*** *and how these characteristics should be* ***combined and integrated*** *into* ***user models****.*

To address this challenge, we relied on an incremental empirical approach, by conducting two studies to analyze the influence of different internal factors on motivation and engagement. First, we determined which player profile is the most relevant to model game preferences for gamification (study described in section 6.2) and then we conducted a second study to determine the influence of this user profile and initial motivation on the variation of motivation and behavioral metrics related to engagement (study described in section 6.3).

6.2. Influence of player profile on motivation in a generic context

The work presented in this section relies on the results of the study conducted during the PhD of Stuart Hallifax and published at the conference CHI-PLAY 2019 [Hallifax et al., 2019a] that I detailed in chapter 4, section 5.2.

As explained previously, recent work on tailored gamification aims to identify links between user types and motivating game elements. However , findings are highly heterogeneous and one reason is that these studies use different typologies to characterize users. To overcome this , we aimed to obtain more generalizable findings. We ran a crowdsourced study with 300 participants to identify the motivational impact of game elements according to users' game preferences, using three different user typologies to characterize users.

6.2.1. Study

In this study, we first question the influence of the use of one particular player type for tailored gamification. Indeed, the results obtained in the different studies are not comparable and designers are not advised on a particular typology or model to use. Furthermore, even if some user types have the same name, they do not have the same definitions, or represent the same user motivations (e.g. Achievers in BrainHex like collecting everything, whereas achievers in Hexad are motivated by mastery). We also question the relevance of considering only the dominant type in player typologies since several recent studies consider all dimensions [Orji et al., 2017b, 2018; Mora et al., 2018].

To address these questions, we explored the influence of game preferences on users' motivation. To measure the motivation of participants regarding game elements, we asked them to rate the different storyboards. We compared variations of participants' interest based on users' profiles according to the three most commonly used user models, using the following questionnaires: BrainHex[1], Big Five Factor (using the TIPI questionnaire [Gosling et al., 2003]), and Hexad[2] [Tondello et al., 2016b, 2019b].

For each user model, we first analyzed the reliability of the dominant user type and then computed the influences of each dimension on the score for each game element. We compared the influences found for each user model dimension in relation to their definitions and to the main results of the related work.

More details on the experimental protocol can be found in the previous chapter (section 5.2) and in the article [Hallifax et al., 2019a].

6.2.2. Results

First, to evaluate the reliability of the dominant user type, we looked at how it affects the perceived motivational impact of the game elements. To do so, we clustered participants according to their dominant user type and calculated the Kendall Coefficients of Agreement

[1] http://survey.ihobo.com/BrainHex/

[2] We used the French version proposed here https://hcigames.com/wp-content/uploads/2019/11/Hexad-Survey-and-Instructions_FR.pdf

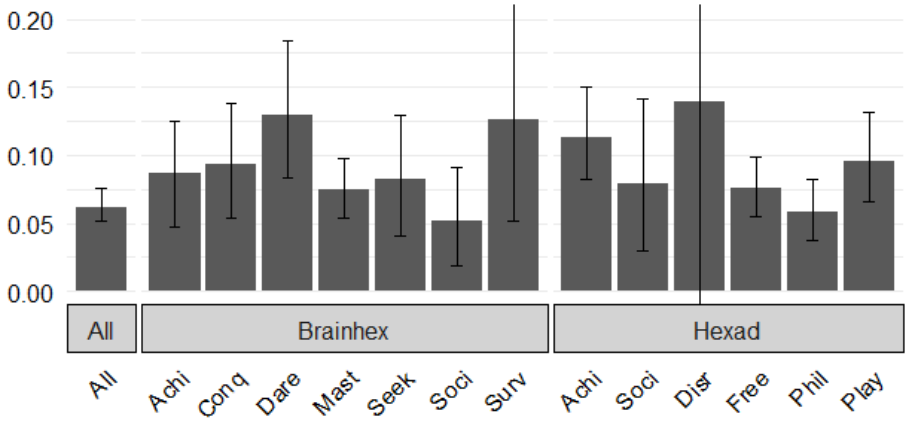


Figure 6.1.: Coefficients of agreement for each dominant type described in [Hallifax et al., 2019a]. The error bars show the 95% confidence intervals.

u within each group. We compared this agreement to the global value obtained on the whole set of participants. As illustrated in figure 6.1, we found the coefficients of agreement within each dominant user type cluster to be low, with no group scoring an agreement greater than 0.15. While most of these values are nevertheless higher than the global one (0.062), this still shows that *dominant user types cannot be considered sufficient to differentiate users according to their game element preferences.* A recent study by Loria and Marconi [2018] also confirms this finding.

Secondly, we more precisely investigated the relationships between each user model and game elements to identify which user typology is the most relevant for identifying user preferences for game elements. To calculate how well each user type affects the scores for each game element, we used the PLS-PM method [Hair Jr et al., 2016; Sarstedt et al., 2017]. This method is based on structural equation modeling to estimate complex cause-effect relationship models with latent variables. The latent variables are not directly observable but are inferred from a set of observed indicators (forming the underlying construct). Usually, these latent variables come from models and theoretical frameworks. For instance, a Hexad user type can be considered as a latent variable inferred from the answers to the four questions defined for this type. The validity of the models can be verified through indicators' reliability, internal consistency reliability, and convergent validity. Relationships between latent variables are then analyzed through the strength and significance of paths (called influences) between the constructs. It is particularly useful in situations where the relationships are complex, and there may be a small sample size or non-normal data distribution.

In this analysis, we constructed and validated three path models, one for each typology, to identify how the values for each user type influence the scores for each game element. The influence values vary between -1 and 1 depending on how strong the effect is. As this is a statistical evaluation, we use the calculated p-value to determine the validity of the given influences. Table 6.1 shows the PLS path coefficients that reflect the positive or negative influence that each user model dimension has on the motivation score of the different game elements.

For *BrainHex*, five user types have significant influences on the different game elements. This can be explained using the definition of the BrainHex typology Nacke et al. [2011] for

		BrainHex							Hexad						Big Five				
Strategy	Game element	Seek	Surv	Dare	Mast	Conq	Soci	Achi	Phil	Soci	Free	Achi	Disr	Play	Extr	Agre	Cons	Emot	Open
Rewards	Badges	.01	-.01	.13	.11	.07	-.07	.02	-.08	.07	.04	.05	-.06	-.07	.00	-.01	.04	-.02	.00
	Points	-.12	.02	.01	-.02	-.08	-.05	-.06	-.06	-.14	.06	-.16	.00	.10	.05	-.07	.04	.04	-.06
	Useful	.11	-.04	.13	-.03	-.08	.02	.10	.03	-.13	.09	-.07	-.02	-.08	-.02	.01	-.12	.03	-.04
Goals	External	-.07	.04	-.04	.09	-.16	.02	.02	.13	-.30	.05	.10	-.05	-.01	.00	.03	.07	-.03	-.04
	Self	.06	.10	-.09	.01	-.10	.10	.01	.12	-.08	.05	.09	.00	-.08	.06	.05	.03	-.03	-.02
Time	Schedule	-.02	.03	-.05	.02	.04	-.07	-.00	.07	-.10	-.07	.03	-.08	-.04	-.05	.04	.06	.03	-.07
	Timer	-.08	.01	.02	-.05	.04	-.07	-.14	-.03	-.04	-.15	.13	.06	.01	.03	-.05	.08	-.03	.06
Social Interaction	Trading	.01	.06	.02	-.05	.10	.11	.04	-.06	.26	.05	.03	-.01	-.06	.03	.12	-.15	.10	.04
	Teams	.02	-.09	.01	-.05	.16	.04	.09	-.05	.34	.01	-.10	-.07	.03	-.05	-.04	-.06	-.06	.19
	Discussion	.08	.07	-.10	.01	.01	.18	.06	.02	.24	.13	-.11	-.07	-.01	-.03	.14	-.06	-.02	.04
Progress	Compared	.01	-.13	.03	.04	-.01	-.08	.01	.02	-.14	-.14	.08	.16	.08	-.02	-.14	.02	.02	-.05
	Task	.02	-.09	-.06	-.06	-.09	-.15	-.12	-.07	-.16	-.11	-.06	.17	.07	-.02	-.12	.07	-.06	-.10

Table 6.1.: PLS Path coefficients for each user type of each typology described in [Hallifax et al., 2019a]. Values in grey are not significant ($p > .05$), highlighted in dark grey are significant ($p < .05$), and highlighted in black are highly significant ($p < .001$).

one type and partially for the others. However , many of our results do not align with the definitions given in the typology. In addition, the definitions of two user types do not seem well-suited for gamification. This result is in line with recent empirical investigations on the psychometric properties of BrainHex that have shown low reliability scores [Busch et al., 2016; Tondello et al., 2018]. This typology was built for games, and there is no evidence of the generalizability of game motivation models to gameful design [Tondello et al., 2017a]. In addition, our results obtained with the BrainHex user typology are quite different from other studies conducted in specific contexts (gamified health system Orji et al. [2014] and experts' recommendations in education [Lavoué et al., 2018]).

Regarding *Big Five* personality model, three traits have significant influences. As with BrainHex , some of our results can be partially explained by the definition of the personality traits, but most of them are not directly in line with the definitions. This result was predictable since Big Five is a general personality trait model and not specifically developed for games or gamification. The comparisons with other studies mainly highlight the differences in the results obtained both (1) between our study and studies conducted in a specific context, and (2) between the studies conducted in different contexts, even in the same domain like health (between Jia et al. [2016] and Orji et al. [2017b] for instance).

Finally, regarding *Hexad*, our results show that four user types have significant influences, one of which is highly significant. Moreover, most of our results are consistent with the definitions of the Hexad typology [Marczewski, 2015]. This result reinforces the fact that this typology was designed especially for gamification and most of its player types are based on SDT [Ryan and Deci, 2000b], the major theoretical foundation for gamification research. As with Big Five, the results with the Hexad types are quite different from those found in studies conducted in different specific contexts (education [Tondello et al., 2016b] and health [Orji et al., 2018]), except for three user types that show similarities.

6.2.3. Summary of contribution

From an empirical point of view, we showed that the motivational impact of certain game elements varies according to the activities or the domain of gamified systems. Our analysis of the influence of game preferences on motivation and the comparison with related work allowed us to identify Hexad as the most relevant user typology to identify user preferences

for game elements. Hexad is also the most consistent with the definitions of its user types. In addition, we demonstrated that for modeling users' game preferences, we cannot rely only on the dominant type. User profiles should thus consider all dimensions of the typology, or at least a combination of player types with the most significant influences. This opens an interesting avenue for future research such as the identification of clusters of hybrid user profiles to consider the impact of a combination of user type scores.

From these findings, we derived some design recommendations on the use of specific game elements according to Hexad dimensions. These relationships between game elements and dimensions of the user profile can be used to specify a precise model of user game preferences. Since we have shown that some game preferences are context-dependent, we also need to rely on empirical data from the domain-specific activity to consolidate and complement specific relationships between profile dimensions and preferences. The following section presents a second study conducted in ecological conditions that provide context-dependent data useful for our model.

6.3. Influence of player profile and initial motivation on final motivation in an educational context

This study was also conducted within the Ludimoodle project. The analysis, resulting from an equal collaboration with researchers from ECP laboratory at Lyon 2 (Stephanie Reyssier, PhD student funded by the project, and Stephane Simonian), was published in IEEE Transactions on Learning Technologies [Reyssier et al., 2022].

The objective was to investigate in real conditions the effects of gamification on learners' motivation and engagement according to both their initial motivation and player profile. In the project, we co-designed the gamified environment with teachers (as presented in the previous chapter, section 5.4), and we conducted an experiment with 258 learners in secondary schools in France. We analyzed the effects of gamification on the variation of motivation and engaged behaviors. We also observed the effect of each game element separately according to learners' profiles.

6.3.1. Study

A total of five teachers and 258 students (14–15 years old) in 12 classes (an average of 25 students per class), from four different secondary schools, participated in the study. Game elements were randomly distributed (one element per student), while respecting parity between genders, classes, and colleges. We ensured that there was no class or gender effect at the outset.

The experiment was conducted over three consecutive weeks. Each lesson was conducted in the same way: 10–15 minutes of written notes (these notes were handed out to learners by the teachers to ensure that they had access to the same content), followed by 25–30 minutes for answering quizzes related to the lesson topic. The learners used individual tablets to access the quizzes. Teachers answered technical questions asked by learners individually. Learners filled out the Hexad questionnaire [Tondello et al., 2016b, 2019b] to determine their player profile, and the AMS) questionnaire [Vallerand et al., 1992] to determine their initial

motivation for mathematics, assessing the seven dimensions of motivation (as presented in Chapter 2).

Learner interactions with the learning environment were tracked using the Moodle data logging system. In order to analyze learners ' engagement, we were interested in distinguishing normal behaviors from expected behaviors induced by the pedagogical scenario (called *motivated behaviors* in the article). In particular, we defined two indicators, one representing engagement for achieving high results for a specific quiz by retrying it after having completed it at least at 70% (Restarted Quiz Count indicator) and the other one representing cognitive involvement in the task by looking at the question ratio of correct and incorrect answers (Question Ratio indicator).

6.3.2. Results

Evolution of motivation

Firstly, we investigated the general effect of gamification on motivation by comparing the variation of motivation of each subscale of the AMS questionnaire considering all game elements, and then according to each game element used (Table 6.2).

We observed a decrease in motivation, especially in *intrinsic motivation to knowledge* and in *external regulation*, as well as a significant increase in *amotivation*.

This result is in line with other studies that have shown a general decline in intrinsic motivation over the long term [Hanus and Fox, 2015; Hamari et al., 2014]. This decrease in intrinsic motivation for knowledge raises questions about the perceived value of the learning activity. It seems that learners perceived the exercises more as a game than as a serious learning activity, which echoes the findings of Barata et al. [2017]. This may also be due to the duration of the study, as teachers testified that some learners were a little bored after eight quiz sessions.

The decrease in external regulation can be explained by the fact that learners motivated by their mathematics grades were frustrated that they did not receive any grades for the quizzes completed during the experiment (a choice made by the teachers for the experiment). The general increase in amotivation means that learners found fewer reasons to do mathematics. This result is similar to that found in a previous study conducted with a gamified learning environment dedicated to learning French grammar [Lavoué et al., 2019]. Learners provided with game elements that were not adapted to their player profile showed higher levels of amotivation. This result could reflect one of the main effects of the learning activity itself, merely moderated by gamification.

Analyzing the effects of each game element separately confirmed these results: there is a decrease in intrinsic motivation to knowledge for all game elements and an increase in amotivation. Badges had even more negative effects, with a decrease in intrinsic motivation for accomplishment and identified regulation. This corroborates the results presented by Hanus and Fox [2015], which suggest that Badges and other rewards are considered as controlling rewards, since they encourage action but constrain it to the objectives proposed by Badges. This perception could degrade learner intrinsic motivation.

Regarding engagement, we also noted differences in motivated behaviors depending on the game elements received. The most significant difference concerns the Timer, which seems to

Game Element		All	Avatar	Badges	Progress	Ranking	Score	Timer
Δ Intrinsic motivations (ΔIM)	ΔKnowledge	-9.769	-4.627	-4.22	-3.747	-4.629	-3.829	-2.969
	ΔAccomplishment	-1.235	-0.121	-2.217	-0.415	-0.703	-0.621	-0.197
	ΔStimulation	-1.261	-0.414	-1.278	-0.019	-1.882	-0.763	-0.33
Δ Extrinsic motivations (ΔEM)	ΔIdentified reg.	-0.128	-0.082	-2.259	-0.197	-0.685	-1.211	-1.322
	ΔIntrojected reg.	-0.659	-0.54	-1.917	-0.534	-0.354	-0.209	-0.809
	ΔExternal reg.	-6.209	-2.976	-3.363	-4.007	-1.448	-0.83	-2.536
Δ Amotivation (ΔAMOT)	ΔAmotivation	10.78	4.125	5.225	3.683	5.397	4.523	3.561

Table 6.2.: Variations of motivation in total and per game element described in [Reyssier et al., 2022]. Wilcoxon signed-rank test values (W). Values in gray are not significant ($p > .05$), values highlighted in light gray are significant ($p < .05$), values highlighted in dark gray are highly significant ($p < .01$), and values highlighted in black are very significant ($p < .001$).

support lower engagement, since learners who used a Timer restarted quizzes significantly less often than the others, with a lower ratio of correct answers.

Influences of initial motivation and player profiles

We used the PLS-PM method [Hair Jr et al., 2016; Sarstedt et al., 2017] to calculate the influence of learner profile, defined by the initial motivation scores and the player type scores, on both motivation (variations in motivations) and engagement (motivated behaviors). Our model is illustrated in Figure 6.2. We ran a PLS path analysis using groups of learners that had the same game element (for instance, Table 6.3 for Timer and 6.4 for Score; the other tables can be found in [Reyssier et al., 2022]).

From an overall perspective, we found that certain game elements degraded the motivation of some learners, as observed when considering the entire group of learners. Only the variation in amotivation and motivated behaviors are positively impacted when using Avatar, Progress, Timer, or Score. When looking at learner player profiles, we noticed that five player types have an influence on the impact of game elements on learner motivation, and that all types of motivation and motivated behaviors are impacted, but in very different ways depending on the game elements involved. The Achiever and Disruptor player types showed the most significant impact.

From a detailed perspective, we analyzed every significant influence for each game element and compared them with related studies. I am presenting here only the results of two game elements to illustrate the different influences that each element can have. Regarding the Timer, we observed a negative influence on intrinsic motivation for learners initially intrinsically motivated to do mathematics but a positive influence on amotivation for the most amotivated learners. The Timer had the greatest impact regarding player profile (except for Philanthropists), involving an increase in both intrinsic and extrinsic motivations for Achiever and Free Spirit learners. Regarding the Score game element, we observed mostly negative influences according to learners' initial motivation and player profile (for both Disruptors and Philanthropists) on intrinsic and extrinsic motivations, as well as on motivated behaviors (Table 6.4). We observed few positive influences, such as the increase of motivated behaviors for intrinsically motivated learners or the increase in extrinsic motivation for Socializers.

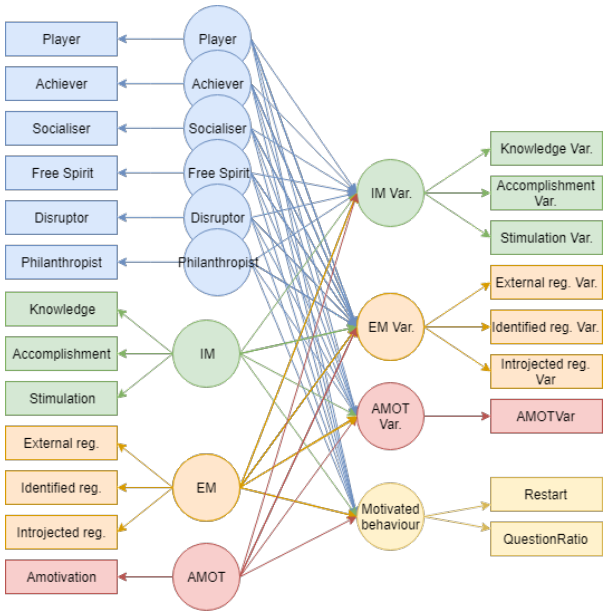


Figure 6.2.: Partial least squares path modeling analysis diagram used in [Reyssier et al., 2022]. In rectangle borders the outer model, and in circle borders the inner model. On the left: the initial profile values of participants (i.e., Hexad profile, initial motivation for mathematics). On the right the observed outcomes (i.e., motivational variations and motivated behaviors)

	Init IM	Init EM	Init AMOT	achiever	player	socializer	freespirit	disruptor	philanthropist
ΔIM	-.571	-.101	.325	.639	.104	.180	-.170	-.228	-.366
ΔEM	-.421	-.111	.288	.689	-.015	.065	.318	-.013	-.407
ΔAMOT	-.325	-.140	-1.112	.097	.056	.124	.073	.011	-.226
Motivated Behavior	.120	.130	.287	.749	.313	.011	-.332	-.222	-.435

Table 6.3.: PLS Path coefficients observed for learners who have received the Timer game element described in [Reyssier et al., 2022]. Values in grey are not significant ($p>.05$), highlighted in light grey are significant ($p<.05$), and highlighted in dark grey are highly significant ($p<.01$)

	Init IM	Init EM	Init AMOT	achiever	player	socializer	freespirit	disruptor	philanthropist
ΔIM	-.909	-.098	-.615	.261	-.202	.208	-.032	.120	-.183
ΔEM	.304	-1.032	-.302	.250	.040	.465	-.030	-.289	-.202
ΔAMOT	-.342	.156	-.752	.041	.208	-.005	-.058	.490	.015
MotivatedBehavior	.786	-.721	-.423	.071	-.127	.131	.168	.204	-.631

Table 6.4.: PLS Path coefficients observed for learners who have received the Score game element. Values in grey are not significant ($p>.05$), values highlighted in light grey are significant ($p<.05$), and values highlighted in dark grey are highly significant ($p<.01$)

6.3.3. Summary of contribution

From an empirical point of view, the results indicate that, overall, the motivation of learners decrease. A more thorough analysis revealed that gamification has a positive impact on the most amotivated learners to do mathematics, although different effects were observed among learners. In particular, we noticed significant influences of their initial level of motivation and their player type on the variation in motivation during the study. We showed that these influences vary according to the game element they used. We can conclude that game elements do not have the same potential to affect learner motivation according to their level of initial motivation, and thus that these initial motivations must be considered if we do not want gamification to be detrimental to learners. These findings confirm that to increase efficiency for this particular context, gamification should be tailored not only to the player profile but also to their level of initial motivation for the learning task.

From a methodological point of view, we used the same statistical approach (using PLS-PM) as for the previous study to identify precise influences of each user profile value on motivational outcomes and engagement, either positive or negative ones. In addition, we used more accurate measures of user experience than in the previous study thanks to the standardized motivation questionnaire and the engagement indicators. This allows us to obtain a fine-grained quantified vision of the influences of user profiles for each game element. From these findings, we can consolidate the relationships between profile dimensions and game preferences to specify user models relying on empirical evidence.

6.4. Discussion

This chapter contributes to my second research challenge, which focuses on modeling users' characteristics, activities, and experience. We conducted two studies in the context of gamification for education. We were interested in investigating the impact of game elements on engagement and motivation, which are the most studied dimensions of UX in this context.

First, from an **empirical perspective**, we believe that the two studies presented in section 6.2 and section 6.3 contribute to a better understanding of the learner characteristics we should consider for user modeling. The lack of deep understanding of the influence of users' characteristics on the effects of gamification was underlined in the research agenda of several systematic literature reviews [Klock et al., 2020; Oliveira et al., 2022b; Rodrigues et al., 2021b].

We adopted an incremental approach. We first focused on investigating the relevance of the most relevant player typology to model game preferences. Secondly, we determined the influence of this typology and initial motivation on the variation of motivation and behavioral metrics.

In the study described in section 6.2, we demonstrated that the Hexad framework [Marczewski, 2015] was the most relevant for gamification and that considering only the dominant user type in a profile was not sufficient to establish reliable correlations between game elements and user profiles. Our results showed that all the dimensions of each profile should be considered to obtain more fine-grained results. I believe that this approach will allow us to specify more precise user models in comparison to the ones used to tailor gamification. Thanks to the second study described in section 6.3, we were able to analyze in depth,

for each game element, the influences of each Hexad user type on the variation of motivation and engagement in a specific activity. These influences can be used then to define fine-grained models for adaptation algorithms (as I will present in the next chapter 7). In addition, we demonstrated that several characteristics should be integrated to specify game elements recommendations : the player profile but also the initial motivation for the activity. Relying on the SDT framework, we are able to propose influences of game elements for each type of motivation in the same way as for player types.

From a **methodological perspective**, we established recommendations of game elements according to user profiles using the influences calculated using the PLS-PM statistical approach. This approach allowed us to identify precise influences (either positive or negative) of each user profile value on different outcomes, allowing us to investigate complex multi-dimensional profiles and the relationship with different outcomes. An interesting element to underline is that using this approach allowed us to observe negative influences on the perceived motivational impact of game elements, whereas most of the other studies only measure positive influences. Regarding the metrics used, we chose to consider the impact of game elements on the variation of motivation before and after the use of the gamified environment in order to be more precise than assessing only the final motivation. To tackle the challenge related to the use of more objective measures to assess the suitability of game elements for users, we investigated the use of two behavioral indicators (question ratio and restarted quiz count).

These first results are promising and open avenues for research related to the integration of user characteristics into models. More studies should be conducted to investigate the impact of game elements on the various forms of engagement, for instance, cognitive, behavioral, or affective engagement if we rely on the definitions presented in Chapter 2). In a three-year longitudinal study, Barata et al. [2017] showed that students could be divided into different clusters based on their behaviors and performance levels. Behavioral and academic outcomes could thus be considered to specify correlations between game elements and users' characteristics to enrich user models.

Our results are based on a context-dependent study using a questionnaire assessing the motivation to learn mathematics. Since the context seems to have an influence on how users perceive game elements as suggested in our first study described in section 6.2 [Hallifax et al., 2019a], another research avenue lies in conducting more studies in different contexts. Having data on different contexts would allow us to investigate the possibility of generalizing some parts of user models, specifying "patterns" of influences following common trends.

Finally, although this approach has been used to study the impact of persuasive strategies on the Hexad profile [Orji et al., 2018] or the BrainHex profile [Tondello et al., 2018], the influences have never served directly as a basis for tailoring algorithms. In the next chapter, I describe how we used these influences to specify an algorithm for tailored gamification.

7. Providing adapted experience: tailored gamification

In this chapter, I present our contributions to tailored gamification for education. This work encompasses my three research axes: firstly, modeling user profiles based on previous analyses (Research Axis 2); secondly, implementing an adaptation algorithm that recommends a game element based on users' characteristics (Research Axis 3); and lastly, understanding how tailored technology influences user behaviors and experiences (Research Axis 1). Adopting an empirical approach, we conducted a large-field study in secondary schools to analyze the effects of the tailoring approach on users' motivation and engagement.

7.1. Challenges in tailoring gamification

Tailored gamification is a current trend that takes into account users' inter-individual differences when gamifying a system [Böckle et al., 2017; Rapp et al., 2019].

As discussed in the previous chapter (section 6.1), one direction of research in tailored gamification is to explore ways to model user profiles, primarily specifying correlations between game elements and user characteristics. From these correlations, the tailoring process generally involves assigning the most suitable game element to the highest score of the user profile [Monterrat et al., 2017; Oliveira et al., 2020, 2022a]. A few works introduced algorithms based on a set of rules predetermined at the design phase, such as Mora et al. [2018], who define different rules to take into account the two highest values of the Hexad profile. Knutas et al. [2017] specify rules based on the dominant user profile (during the design phase) combined with user interactions (during the use of the system). This leads to a variety of models and approaches in the literature, and the results of the studies investigating the impact of tailored gamification seem very dependent on the user model used to assign the most suitable game elements to users.

Thus, little is known about the relevance of each user model in comparison to the others in the tailoring process and how combining several models could allow considering different preferences simultaneously. Yet, as identified in the previous chapter, correlations between game elements and both player preferences and the initial motivation for the activity were observed.

Therefore, we believe that one challenge is to investigate how adaptation algorithms could take into consideration different user models (including combination of several profiles) and analyze if the effects on UX are dependent on the user model chosen.

Another research direction is to explore the effects of tailored gamification. Some studies compare tailored gamification with one-size-fits-all gamification, as reported in the systematic literature review on personalized gamification [Rodrigues et al., 2021b]. The authors

report mixed results for motivational, behavioral, and cognitive outcomes. Other recent literature reviews on tailored gamification in education [Hallifax et al., 2019b; Oliveira et al., 2022b; Bennani et al., 2022] also identify mixed results.

Roosta et al. [2016] showed significant differences in motivation, engagement, and quiz results between learners that used an adapted (to their motivation) or a randomized game element. Hassan et al. [2021] also showed that learners who used game elements adapted to their learning style reported higher motivation rates than those who used random game elements. Mora et al. [2018] reported an increase in students' behavioral and emotional engagement when adapting to their Hexad player type. Finally, Rodrigues et al. [2021b] showed that the students using a personalized design were more motivated than those using the one-size-fits-all approach regarding intrinsic motivation and identified regulation. More mixed results are reported. For example, Monterrat et al. [2017] showed that the adaptation process had a negative impact on the perceived usefulness and fun of gaming features. However, in a similar study, Lavoué et al. [2019] found that providing learners with adapted game elements made the most engaged learners spend significantly more time in the learning environment. In another study, Paiva et al. [2016] analyzed the usage data during the month after the introduction of tailored goals in their learning tool used for learning mathematics. The results showed that only specific goals were effective in increasing the number of related actions. Finally, Oliveira et al. [2020] found no differences between adapted and non-adapted conditions on learners' flow experience. This finding is somewhat contradictory with a previous study Oliveira and Bittencourt [2019] in which the same authors found that for some player types, the tailored system induced better learner concentration than the counter-tailored one, while for other player types the counter-tailored game elements functioned better.

In conclusion, these studies report mixed results when adapting gamification to learners, highlighting the need for more empirical studies on this recent research issue [Klock et al., 2020; Oliveira et al., 2022b; Rodrigues et al., 2021b]. There is no consensus on the effect of gamification, and this effect may vary depending on the type of game elements used and on the context of deployment, as underlined by Hallifax et al. [2019b]. We believe that there is a need to investigate more deeply which learner characteristics should be considered in the adaptation process depending on the game element used. We agree with Bennani et al. [2022] that it is crucial to take into account different changing aspects such as learners' motivations, and not only player types, to understand which mechanisms and dynamics can enhance their motivation in specific contexts. In addition, motivation is generally approached as a whole, or by differentiating only between intrinsic and extrinsic motivations, when it is a very complex concept that can be defined in multiple ways as previously presented [Deci and Ryan, 1985b; Vallerand et al., 1992; Vallerand, 1997].

Thus, another challenge is to better understand the effect of gamification on the different types of motivation, as well as their evolution over time, to take into account the complex and evolving nature of motivation.

Moreover, as underlined by O'Brien and Toms [2008], engagement also has a cyclical nature, with potential points of engagement, disengagement, and re-engagement. However, as noted in Hallifax et al. [2019b], studies generally focus on the effects of adapted gamification on learners' motivation and performances after using the learning environment, but do not investigate if and how tailoring game elements affect their behaviors while performing the learning activity. This is also underlined by Klock et al. [2020], who state that tailored gamification could be improved by considering how learners' interactions with the learning environment evolve over time. This can be investigated through the lens of behavioral

engagement, as defined in Chapter 2 [Fredricks et al., 2004; Reschly and Christenson, 2012] and usually measured by observable actions of the learner when completing an activity [Linnenbrink and Pintrich, 2003]. As underlined in section 2.2 on engagement measures, recent works have started to investigate behavioral patterns extracted from data logs [Codish and Ravid, 2015; Fincham et al., 2019]. Other works focus on analyzing the evolution of simple indicators over time to better characterize behavioral engagement [Barata et al., 2017; Taşkın and Kılıç Çakmak, 2022]. We believe that combining indicator-based exploratory methods and temporal analysis should offer a promising approach for a comprehensive evaluation of learners' engagement over time.

Thus, the last challenge is related to the investigation of methods to analyze behavioral engagement over time to improve our understanding of learners' engagement while performing the activity.

To address these challenges, we developed an algorithm that combines the user models described in section 7.2 to recommend the most suitable game element to the user characteristics. We conducted a second large-scale study in real class settings using the proposed adaptation algorithm . We ran two different analyses on the data collected during the experiment: one to analyze the effects of tailored gamification on motivation over time and one on the effects on engagement over time.

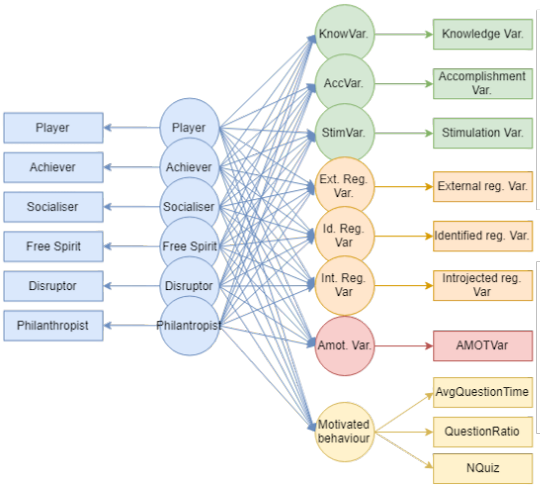
7.2. Adaptation algorithm

We proposed an adaptation algorithm published in AIED 2020 [Hallifax et al., 2020] based on the empirical data from previous studies presented in Chapter 6. We first proposed a method to model users' preferences for game elements based on the analysis of the influences of the different profile dimensions. We investigated different ways to adapt game elements according to the player profile, the initial learner motivation, or a dual profile combining both player type and initial motivation. To measure the effects of such adaptation, we used the data from the previous experiment by simulating the different adaptation techniques.

7.2.1. User model

From the previous study presented in section 6.3, we proposed a method to model users' preferences for game elements based on the analysis of the influences of the values for each user type (for both player profile and initial motivation) on the variations for each motivation type and engagement, using PLS-PM approach [Hair Jr et al., 2016].

For each single profile, we generated an *affinity matrix* representing how each profile value affects the appreciation for each game element. To do so, we ran two PLS-PM models between the profile values and the variations of motivations for each subset of learners that used a particular game element. The models were similar to those used for the previous analyses, except that we treated both the Hexad player profile and the initial motivation profile independently with two distinct models (Figure 7.1 illustrates the PLS-PM model for Hexad). This provided us with six matrices of influences for each profile (one per game element, and an example for the Avatar game element is given in Table 7.1 for the Hexad profile). To obtain the final affinity matrix for each profile, we combined the six matrices of each game element. To do that, we summed each value of influence (except for the amotivation value that we subtracted). For example, to obtain the influence value of the Player profile on Avatar, we



	Player	Achiever	Socialiser	Free Spirit	Disruptor	Philanthropist
Know.Var.	0.329	-0.356				
Acc.Var.	0.541		-0.521			
Stim.Var.						
Ext.Reg.Var.						
Id.Reg.Var.						
Int.Reg.Var.						
Amot.Var.						
Behaviours						0.396

Table 1. The influence matrix for the Hexad profile, with the avatar game element.

	Player	Achiever	Socialiser	Free Spirit	Disruptor	Philanthropist
Avatar	0.870	-0.356	-0.521			0.396
Badges			-0.548	-1.233		1.229
Progress		-0.011	-0.331		-0.061	
Leaderboards			-0.459		-0.870	
Points	0.490		-0.467			-0.694
Timer		1.772	0.439	0.530	0.398	-1.125

Table 2. The final affinity matrix for the Hexad profile

Figure 7.1.: Model and matrices for Hexad profile described in [Hallifax et al., 2020]. Left : PLS-PM Model for creating the Hexad influence matrices. Right top: The influence matrix for avatar. Right bottom: The final affinity matrix for Hexad profile.

summed the value of both influences on intrinsic motivation (0.329 + 0.541 = 0.870), while the other influence values were not statistically significant. The final affinity matrix demonstrated for each game element how important a given profile metric is in its influence. The full affinity matrix for the Hexad Profile is given in Figure 7.1. We applied the same process to obtain the affinity matrix for the initial motivation profile.

Thanks to these matrices, we were able to assign a game element for each learner according to the value of their profile. For the dual adapted model, we used an algorithm to find a compromise between the two single profile recommendations.

7.2.2. Algorithm description

Figure 7.2 presents an overview and example of how the adaptation works.

The algorithm is based on the two affinity matrices presented previously. To recommend a game element based only on one profile (either the player profile or the motivational profile), we multiplied the individual learner profiles with these influence matrices. This gave us two ”affinity” vectors for each learner (one based on each profile). These affinity vectors show how well suited each game element should be for a given learner. To recommend a game element considering the dual profile user model, we used a compromise algorithm based on both player and motivation profiles. The algorithm first checks for positive affinity overlaps between the two affinity vectors. If any game elements have positive affinities in both vectors, it combines the ranks of these game elements, selecting the lowest ranked game element. If there is no game element in this overlap, it then combines the rankings of the affinity vectors for all game elements (again selecting the lowest ranked). If at any point there is a tie for the lowest rank, it adds the affinities from both vectors and selects the game element with the highest affinity. We chose to rely on ranking rather than directly on the affinity values because the generally motivation values were much higher.

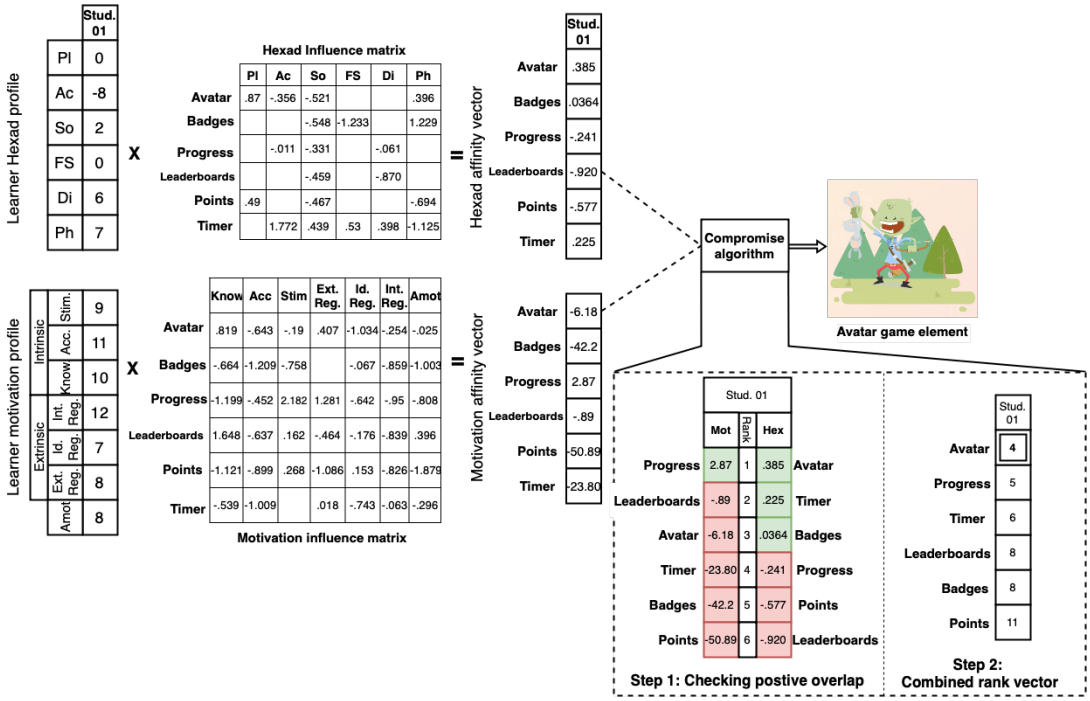


Figure 7.2.: Learner adaptation process described in [Hallifax et al., 2020]. Both the learners' Hexad and initial motivation profiles are used to adapt using the compromise algorithm. In this example, we show how Student 01's profiles are used to recommend the Avatar game element: both the Hexad and Motivation influence matrices are obtained by adding the individual partial least squares result matrices for each game element. There is no positive overlap in the affinity vectors, so we combine the rankings for each game element.

For example, for a learner with the Hexad profile (Pl:0; Ac:-8; So:2; FS:0; Di:6; Ph:7), we normalize the values of their profile and then obtain the following affinity vector ('Avatar': .385, 'Badges': .0364, 'Progress': -.241, 'Leaderboards': -.920, 'Points': -.577, 'Timer': .225). We would therefore recommend the Avatar game element. The same learner with the following initial motivation for mathematics (Mico:9; Miac:11; Mist:10; ExtReg:12; IdReg:7; IntReg:8; Amot:8) would have this affinity vector: ('Avatar':-6.188; 'Badges':-42.22; 'Progress':2.871; 'Leaderboards':-0.899; 'Points':-50.899; 'Timer':-23.807). As there is no positive overlap in these vectors, we combine the rankings for all game elements resulting in ('Avatar':4; 'Progress':5; 'Timer':6; 'Leaderboards':8; 'Badges':8, 'Points':11) and would therefore recommend the Avatar game element (see figure 7.2).

7.2.3. Algorithm validation

We used the data collected for the study presented in section 6.3, where learners were assigned a randomly game element. We then simulated three adaptation techniques using the profiles of these 258 learners. From this set, we constructed the following data subsets:

- Hexad data subset: 42 learners used game elements adapted to their Hexad player profile (216 did not).

- Initial motivation data subset: 45 learners used game elements adapted to their initial motivation (213 did not).
- Dual profile data subset: 42 learners used a game element recommended by the dual profile algorithm (216 did not).

To measure the effects of each adaptation technique, we used the metrics on motivation and engaged behaviors calculated in the previous study: the variations of the different types of motivation, the average time to answer a question (AvgQTime), the ratio of correct versus incorrect answers to a question (QRatio), and the number of quizzes attempted (NQuiz). Table 7.1 presents the results of the different simulations.

Metric	p	Adapt.	Non
Know.Var.	.233	-1.489	-2.099
Acc.Var.	.289	0.422	-0.352
Stim.Var.	.458	0.289	-0.263
Id.Reg.Var	.447	0.289	-0.117
Int.Reg.Var	.492	0.222	-0.282
Ext.Reg.Var	.482	-1.089	-1.235
Amot.Var.	.619	2.267	2.953
AvgQTime	**.016**	**60.73**	**67.78**
QRatio	**.010**	**0.608**	**0.665**
NQuiz	0.792	34.56	35.33

(a) Hexad

p	Adapt.	Non
.022	**-1.156**	**-2.169**
.008	**0.756**	**-0.423**
.335	0.267	-0.258
.383	-0.400	0.0282
.233	0.378	-0.315
.141	-0.667	-1.324
.867	2.956	2.808
.066	71.42	65.51
.224	0.637	0.659
.189	34.18	35.41

(b) Motivation

p	Adapt.	Non
.052	-1.326	-2.137
.056	0.739	-0.425
.045	**0.848**	**-0.387**
.691	-0.283	0.005
.445	0.326	-0.307
.476	-1.043	-1.245
.012	**1.391**	**3.146**
.812	68.07	66.21
.137	0.630	0.661
.923	36.17	34.98

(c) Dual profile

Table 7.1.: Results for different simulations described in [Hallifax et al., 2020]. The values given are the averages for each group. In light grey: no significant differences, in bold and highlighted in grey: significant at $p<.05$, and highlighted in light grey: almost significant $p\approx.05$

Compared to randomly assigned game elements, tailoring game elements to the Hexad profile had two contradictory effects on behavioral engagement (see Table 7.1). Learners answered more quickly (observed also in [Mora et al., 2018]), but they got more questions wrong (in contradiction to [Kickmeier-Rust et al., 2014]). No effect on learner motivation was observed, similar to the findings in Monterrat et al. [2015].

Conversely, tailoring according to the initial motivation profile had no significant effects on learner engaged behaviors. However, this technique had significant positive impacts on the variation of two kinds of intrinsic motivation (consistent with Roosta et al. [2016] and Hassan et al. [2021]). This result confirms the benefit of using learner motivation for tailoring gamification.

Finally, combining both profiles for the dual adaptation reinforced the observed results with initial motivation, but also led learners to be more motivated to learn mathematics for fun or excitement. This finding aligns with previous studies on the impact of tailored gamification that showed an increase in perceived fun Monterrat et al. [2015] or flow induced by some game elements depending on the player types dos Santos et al. [2018]. Dual adaptation also reduced learner amotivation to learn mathematics, which is consistent with the findings of the study conducted by Lavoué et al. [2018] when adapting only to player types.

7.2.4. Summary of contribution

From a technical and design perspective, we developed an algorithm that recommends a game element for a specific user profile. The algorithm can recommend game elements according to different profiles (player type, initial motivation, or dual profile) relying on affinity matrices generated using a statistical approach based on empirical data.

From an empirical point of view, we demonstrated that the user model chosen to tailor game elements can have significant effects on learners, but on different metrics depending on the chosen profile. Tailoring gamification to initial motivation can induce a more positive variation of intrinsic motivation, whereas tailoring gamification to the Hexad profile led to contradictory results on engaged behaviors. Finally, we showed that a combination of player profile and initial motivation can lead to a more positive variation of intrinsic motivation and less amotivation compared to tailoring based only on initial motivation.

The results obtained in this study were derived from simulations on data from a previous field study where learners had a randomly assigned game element. Our next step was therefore to use the adaptation algorithm with new learners and investigate the effects of tailored gamification in real class settings. I describe in the following sections the new field study conducted (section 7.3) and the analyses performed with the collected data (section 7.4 and section 7.5).

7.3. Study of the impact of tailored gamification over time

During the Ludimoodle project, we conducted a second large-scale field study in real-world classroom conditions using the same Moodle-based platform. A total of 236 learners (aged between 13-15 years old) divided over nine classes in five different French secondary schools participated in our experiment.

Before the use of the learning environment, we first asked learners to fill out the Hexad questionnaire [Marczewski, 2015][1] to determine their player profile and the AMS [Vallerand et al., 1992] questionnaire to determine their initial motivation for mathematics.

Learners were then sorted into one of two experimental conditions. In the *control group*, learners were randomly assigned a game element. In the *experimental group*, learners were assigned a game element tailored to their profile. We used the algorithm presented previously (section 7.2) to determine the most relevant game element for each learner based on both their player type and motivation. Only one condition was assigned to each class so that the users were homogeneous within the same class. Once assigned a game element, they used it for the entire experiment duration.

Then learners participated in the lessons once or twice a week over four to six weeks. They accessed the quizzes individually using tablet devices. Each lesson followed the same format: teachers gave a short introduction to the lesson's topic (10-15 minutes depending on the complexity). Learners then logged into the gamified learning platform to solve quizzes related to that lesson (25-30 minutes).

[1] we used the French version proposed here https://hcigames.com/wp-content/uploads/2019/11/Hexad-Survey-and-Instructions_FR.pdf

After five sessions, during a formative assessment session, learners completed the motivation questionnaire a second time. After the final session, learners filled out the motivation questionnaire a third time. This allowed us to track learner motivation more accurately and identify the variations during the first and second periods of the experiment.

7.4. Effects of tailored gamification on motivation over time

The first analysis that we conducted with the collected data aimed to provide insights on how tailored gamification can affect specific types of learner motivation over time, depending on the game element integrated into the learning environment. To do so, we compared the variations of motivation, distinguishing 6 different types of motivation and amotivation, between the two experimental conditions and for each game element.

This work was done in collaboration with researchers from the ECP laboratory at Lyon 2 (Stephanie Reyssier, PhD student funded by the project, and Stephane Simonian) and was published in the International Journal of Interactive Learning Environments [Dumas Reyssier et al., 2023].

7.4.1. Analysis procedure

For this analysis, we filtered participants to ensure data consistency. We considered only data from learners who had 1) answered the three questionnaires; 2) completed all the lessons. Those that did not satisfy these two conditions were removed from the analysis. Data from 121 learners were processed (58 self-reported female, 63 male), 83 learners were in the adapted condition and 38 in the non-adapted condition. We present in Table 7.2 the number of participants who were assigned one of the available game elements. The students in the control group who received the correct element (i.e., the element that would be assigned by the algorithm) are counted towards the experimental group.

Condition	Avatar	Timer	Progress
Non-adapted	12	11	15
Adapted	14	51	18

Table 7.2.: Number of students per condition, per game element described in [Dumas Reyssier et al., 2023].

We performed Wilcoxon rank-sum tests to compare the variations of each type of motivation between the group of learners who used an adapted game element and those who used a randomly one (within-group comparison). We also performed Kruskal-Wallis tests to compare each motivation variation between the two groups (between-group comparison) for the whole experiment but also for two periods: the first variation (difference between pre- and mid-tests) and the second variation (difference between mid- and post-tests). Here, I report only a portion of the results; all tables are available in the paper.

		First part		Second part	
		Adapted	**NonA**	**Adapted**	**NonA**
Intr.	Know.	-0.18	-0.63	0.7	0.76
	Accom.	-0.38	-0.05	-5.42	-5.97
	Stim.	-0.03	-0.02	2.24	1.34
Extr.	Id. Reg.	-0.17	-0.66	-2.17	-1.19
	Int. Reg.	-0.6	0	0.87	0.64
	Ext. Reg.	-0.21	0.07	-2.72	-1.81
Amot.	Amot.	0.3	-0.23	5.29	6.07

Table 7.3.: Mean variations of the different motivation types described in [Dumas Reyssier et al., 2023]. We calculated the variations in the **First** (*Mid test-Pretest*) and **Second** parts of the experiment (*Posttest-Mid test*). The results are presented for the adapted condition (column **Adapted**) and the non adapted condition (column **NonA**). The cells are colour coded based on the results of the Wilcoxon test: values in grey are not significant ($p>.05$), values highlighted in light grey are significant ($p<.05$), in dark grey are highly significant ($p<.01$), and black are extremely significant ($p<.001$).

7.4.2. Results

General effects of gamification

Within each condition (within-group comparison), we observed significant effects of the use of the gamified environment on several types of motivation with the same trends in both conditions, although adaptation seems to reinforce the observed effects on learners' motivation (significance of results higher for the adapted condition).

The first trend concerns the increase of learners' *intrinsic motivation for stimulation* and the small increase of *intrinsic motivation for knowledge*, whether the elements are adapted or not, showing that, at the end of the experiment, learners were having more fun and were more interested in learning mathematics. The second trend concerns the decrease of other motivation types and the increase of amotivation, in a similar way to the trends observed in the first experiment presented in Chapter 6. This can be explained by the increase in difficulty in the learning content (for intrinsic motivation for accomplishment), the absence of grades during the experiment (for external regulation), and the weariness effect due to the fact that all the sessions were about the same math concept and based on the same type of exercise (for amotivation).

When comparing our results with other similar studies, the increase of amotivation is in line with other studies [Lavoué et al., 2019]. Regarding intrinsic motivation, some studies showed a general decline of *intrinsic* motivation after long-term [Hanus and Fox, 2015; Hamari et al., 2014] whereas others showed an increase [Rodrigues et al., 2021a]. These differences in findings between studies could be explained by different contexts and durations, but also by the fact that they focus on *intrinsic* motivation as a whole. As we tracked a wide variety of motivation types, we were able to analyze more precise variations in intrinsic motivation showing that both trends are partially corroborated.

Differences between tailored and non-tailored gamification

One major finding of our study is that *adaptive gamification has no significant effect on the global variations of motivation compared to randomly assigned game elements*. The level of motivation at the beginning of the experiment was rather the same for the two groups in each type of motivation and no significant differences were observed between the variations of motivation (between-group comparison).

The only difference between conditions was the significant positive effect on *introjected regulation* for the adapted condition, while the randomly assigned game elements did not. This increase in learners' sense of self-esteem [Vallerand et al., 1992] could be explained by game elements that, when adapted, provided more positive or more appropriate feedback to learners.

Effects only visible after several lessons

When considering both conditions, whether the game elements were adapted or not, *we saw significant effects on learner motivation only during the second period of the experiment* (Table 7.3) with the same trends as for the global variations. We believe that learners could have been affected by a novelty effect of introducing a new technology in the classroom which faded away after a while, as mentioned in several studies such as [Hamari et al., 2014; Hallifax et al., 2019b; Sanchez et al., 2020; Rodrigues et al., 2022a]. Another explanation is related to the fact that the learning content increased in difficulty the further learners progressed through the quizzes, leading to harder lessons in the second part, also highlighted in studies such as [Landers et al., 2017].

7.4.3. Summary of contribution

From an empirical point of view, this study in real-class settings first shows that the effects of gamification became visible only after the first five learning sessions. This result demonstrates the need to conduct longitudinal studies and to consider motivation as a process evolving over time, similar to engagement. Second, when considering the second period of the experiment, gamification (either adapted or not) had positive effects on two types of intrinsic motivation (for knowledge and stimulation), while detrimentally affecting other types of intrinsic and extrinsic motivation and amotivation. Third, even if we did not observe significant differences between the two conditions, adapting gamification to learners seems to reinforce the effects on their motivation.

Our results reinforce the idea that future work should consider motivation with a multidimensional approach, which would allow to observe more specific effects of gamification on learner motivation and to achieve a better understanding of gamification.

7.5. Effects of tailored gamification on engagement over time

The second analysis aims to achieve a better understanding of behavioral outcomes of tailored gamification. While most existing studies focus on the analysis of the effects of tailored gamification after using the learning environment, we analyze the impact of adapting game

elements integrated into a learning environment on learners' engagement across learning sessions and its evolution over time.

We performed a factor analysis on the interaction logs collected during the experiment to identify behavioral patterns when using the gamified digital learning environment. We also compared the levels of engagement between learners who used an adapted game element and those who used randomly assigned elements.

This work has been published in the journal *Proceedings of the ACM on Human-Computer Interaction* (PACMHCI) and presented at the CHIPLAY 2023 conference [Serna et al., 2023].

7.5.1. Analysis procedure

Engagement indicators

Learners' interactions with the learning environment were tracked using the Moodle data logging system. As described in section 2.2 on engagement measure, we followed the classic learning analytics approach to specify indicators from data logs, similar to [Codish and Ravid, 2015; Lavoué et al., 2021; Rodrigues et al., 2022a]. The indicators defined focus on how learners were interacting with the gamified system. These indicators represent behavioral outcomes related to quiz completion, feedback on answers, and interaction with the game element. These types of indicators are usually used to measure accuracy, time on task, number of exercises completed [Fincham et al., 2019; Lavoué et al., 2021; Rodrigues et al., 2022a; Taşkın and Kılıç Çakmak, 2022]. For some of the indicators, we decided to use ratios (obtained by dividing the count by the number of quizzes/questions attempted) instead of direct counts, since learners did not attempt the same number of quizzes. All these indicators were calculated either for all lessons or for a given lesson.

Engagement model

We filtered participants to include only those who were present in at least four of the six lessons, leaving us with a total of 145 learners (72 self-reported as female, 73 as male, aged between 13-15 years old). Regarding experimental conditions, 93 learners used an adapted game element (including those who were randomly assigned an adapted one), and 52 used a non-adapted game element.

We then adopted an exploratory approach using a factor analysis to establish an engagement model based on the indicators previously defined. Building upon recent studies (in particular [Fincham et al., 2019]), we had previously tested this approach and were able to identify two types of engaged behaviors from data logs in [Lavoué et al., 2021]. We thus propose the following workflow to obtain an engagement model:

1. We split our data into two equally sized random samples (training and test datasets).
2. We conducted a parallel analysis scree plot on the first half of the dataset (training set). This provided an indication of how many factors we should look for in the following steps.

3. We ran an exploratory factor analysis (EFA) [Field et al., 2012] using the recommended number of factors from step 1 on the training set. We conducted this process in an iterative manner, removing variables that did not load or exhibited factor loadings greater than 1 (as in Costello and Osborne [2005]). We also defined a cut-off of 0.5 so that our factors were clearly and strongly defined Beavers et al. [2013].
4. Finally, we assessed the fit of this model using a confirmatory factor analysis (CFA) on the second half of the dataset (test set).

Statistical comparisons

We calculated an engagement score for each factor using the loadings identified by the EFA: for example, the score for factor 1 is calculated as $-0.681 * AvgQuestionTime + 0.961 * NQuiz + 0.630 * NPassedQuiz + 0.507 * GameElementInfo$. We clarify that we are not interested in these individual scores themselves as they are just the linear combinations of the relevant indicators.

We then compared the scores obtained for each factor in the adapted and non-adapted conditions for all lessons and for each lesson using Wilcoxon rank-sum tests. We then used a pairwise Wilcoxon signed-rank test to compare the evolution of learners' engaged behaviors lesson after lesson in each condition. For this final comparison, we restricted our sample to the learners who were present in all of the lessons (99 learners in total) to be able to compare lessons in pairs.

7.5.2. Results

Behavioral patterns representing different types of engagement

The parallel analysis using the training set suggested a three-factor structure, and the EFA provided us with a three-factor model that uses 9 different indicators out of the 10 defined previously. The standardized loadings for this model are presented in Table 7.4. We then performed a CFA using this model on the other half of the original data (test set).

These results show that we can identify behavioral patterns from learners' interactions with the gamified learning environment. We identified three patterns that we believe correspond to three kinds of engaged behaviors:

F1 (Trial and Error pattern): Learners followed a trial and error method, favoring discovering the learning content, answering questions quickly, trying out lots of quizzes, and reading more about how their game element works. It is important to mention that in education, trial and error can be a sign of learners who do not know what they are doing, or are operating without a useful heuristic or theory of action. However, in game spaces, players are encouraged to try, fail, and retry to progress. In fact, freedom to fail has been documented as an important facet of gamification Strmečki et al. [2015] and echoes the need for autonomy in SDT.

F2 (Improvement by repetition pattern): Learners who behaved in this way were concerned with improving their performances and "perfecting" quizzes. They would complete the minimum required grade and restart the same quizzes to try and obtain 100% over and over again until they achieved perfection. This type of pattern seems recurrent

Indicator	Factor1	Factor2	Factor3
AvgQuestionTime	-0.681		
NQuiz	0.961		
NPassedQuiz	0.630		0.643
NLoop		0.923	
QuestionRatio			0.953
StreakRatio		-0.520	
LessonRatio			0.743
GameElementInfo	0.507		
RestartedQuizzesRatio		0.864	
FeedbackTime			

Table 7.4.: EFA Standardised Loadings obtained in [Serna et al., 2023]

in learning situations, as it is similar to the "Perfection-oriented engagement" that we identified in the first experiment [Lavoué et al., 2021] and the repetition behavioral pattern identified in Codish and Ravid [2015]. We believe that this behavior is linked to the basic need for competence in SDT Ryan and Deci [2000b], and that it is influenced by the motivational affordances related to the design of the game elements. This aligns with findings from other similar studies where game elements have increased the feeling of learners' competence [Sailer et al., 2017; Zainuddin, 2018; Landers et al., 2017].

F3 (Perfection pattern): Learners who behaved in this way got more questions directly right. Thus, they aimed to complete quizzes with the best possible performance on the first try. This behavior is similar to the "Achievement-oriented engagement" that we proposed in the first experiment [Lavoué et al., 2021], as it contains similar indicators with similar rates, and could be related to the need for competence in SDT Ryan and Deci [2000b]. Several studies report correlations between users' activity (assimilated to their engagement) and their performance Denny et al. [2018]; Sanchez et al. [2020], showing that students with gamified quizzes had significantly better scores on the first attempt.

Evolution of learners' behaviors and effects of tailoring gamification

Figure 7.3 shows the evolution of the scores of each behavioral pattern over the sessions in both the adapted and non-adapted conditions, and Table 7.5 shows the significant variations of engagement between lessons for each condition.

Overall, learners' engagement gradually decreased over time, with some nuances depending on each engaged behavior type. An interesting finding in our results is the fact that adapting game elements to learners' profiles seems to have mitigated their loss of engagement. Differences between both conditions can be observed at a global level for two behavior patterns: *Improvement by repetition* and *Perfection*, and for *Trial and error* in the second half of the experiment.

The decrease in the *Trial and error* pattern was more or less constant throughout the experiment. This means that over time, learners attempted and completed fewer quizzes as they

	F1		F2		F3	
Δ Less.	Adapted	Non-Adapt.	Adapted	Non-Adapt.	Adapted	Non-Adapt.
1-2	3.67E-07	1	0.51762609	1	0.78789906	3.46E-05
2-3	0.00765948	8.44E-05	1	1	0.15917534	1.74E-05
3-4	0.22408222	0.01780689	1	1	1	1
4-5	3.67E-06	0.00029995	1	0.87331821	0.01968939	1.05E-08
5-6	1.30E-06	4.40E-06	1	0.64323273	0.00060812	0.02072849
1-6	2.52E-11	3.49E-09	9.12E-05	0.00833137	3.69E-11	0.09281302

Table 7.5.: Variations of engagement between lessons for each condition in [Serna et al., 2023]. p-values of the wilcoxon tests between average engagement values of lessons for each situation, corrected with Bonferroni correction. In grey $p>.05$, in black $p<.05$, highlighted in grey $p<0.01$, highlighted in black $p<.001$

progressed, spent more time on questions, and checked their game element info less. Learners who followed this behavior with randomly assigned game elements were significantly less curious and experimental in their approach than those who had game elements adapted to their profile.

The *Improvement by repetition* pattern was somewhat stable throughout the experiment (if we look on a lesson-by-lesson basis). However, when looking at the difference between the first and the last lesson, we observe a significant decrease. Learners in the adapted condition were generally more *stubborn* in their approach than learners in the non-adapted condition in the last lesson. Adapting the game elements to their preferences for game mechanics and initial motivation for mathematics made them more focused on each quiz and determined to achieve 100%.

Finally, for the *Perfection* pattern, learners in the adapted condition saw a more stable decrease, but those in the non-adapted condition were more erratic, with decreases and increases throughout the experiment. However, there is no significant difference between the first and the last lessons, meaning that even if there were a lot of changes throughout the experiment, there were no significant changes overall for this condition. On average, learners in the non-adapted condition showed higher engagement scores than learners in the adapted condition. This finding echoes the study conducted by Oliveira and Bittencourt [2019], which found that concentration was improved in the counter-tailored condition for some player types. We believe that the lack of variety in the learning content contributed to the decrease of engagement for this behavioral pattern (weariness effect), meaning that gamification (whether adapted or not) might have had less of an effect than for the other two patterns.

7.5.3. Summary of contribution

From an empirical point of view, our results reveal that (1) we can distinguish three behavioral patterns corresponding to different kinds of engaged behaviors, (2) learners' engagement behaviors gradually decreased over time, but (3) adapting the game elements to learners seemed to reduce this decrease or make it more stable, depending on the behavioral patterns, as learners in the non-adapted condition showed a higher decrease than those in

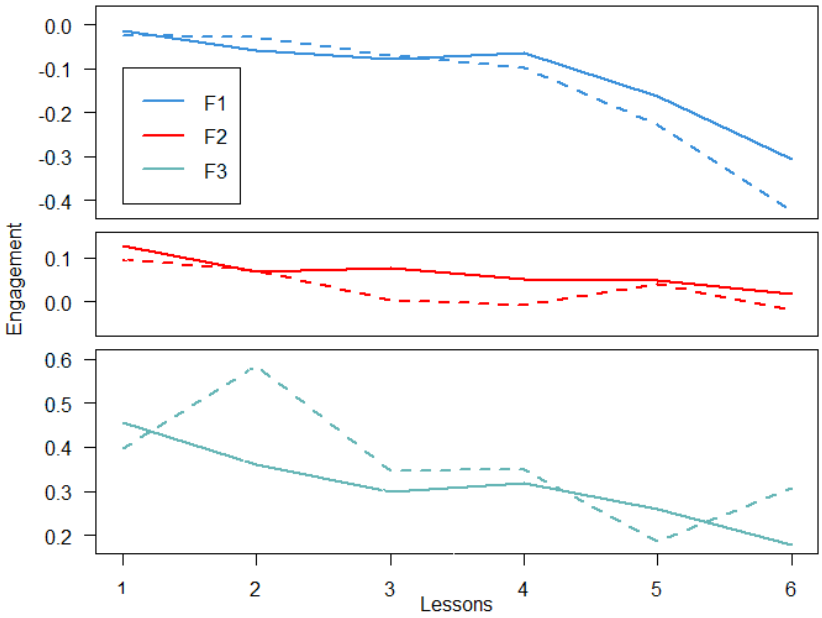


Figure 7.3.: Evolution graph for the engagement factors described in [Serna et al., 2023]. Solid lines represent the learners in the adapted condition, dashed those in the non-adapted condition

the adapted condition (specifically with regards to two of the three identified patterns). Several longitudinal studies also reported a decrease in engagement or performance in the long run [Hanus and Fox, 2015; Rodrigues et al., 2022a]. In this study, the general decrease in engagement could be explained by the same reasons as for the previous analysis on motivation: the increasing complexity of the learning content, and the lack of novelty or weariness effect.

From a methodological perspective, we proposed a method for a comprehensive evaluation of learners' engagement over time. We rely both on a learning analytics approach with the extraction of simple indicators and an exploratory method to identify behavioral patterns from these indicators. Then, by computing an engagement score for each behavioral pattern, we were able to analyze their evolution over time.

7.6. Discussion

This chapter contributes to my three research axes, and more specifically to Research Axis 3, which focuses on providing tailored and adaptive interactive systems. I presented an adaptation algorithm that recommends game elements according to different user characteristics. A large-scale study conducted in real class settings allowed us to perform two analyses on the effects of tailored gamification on user experience. The contributions are mainly technical, empirical, and methodological.

From a **technical and design perspective**, we proposed a new approach to consider and combine different user profiles to recommend game elements. We implemented a compromise between two profiles (initial motivation and player profile) that offered promising results on motivation with simulation data. However, as developed in the empirical perspective, we did not observe such good results in the study in real conditions with new learners. In addition, the algorithm recommended only three game elements out of the six available to the participants. The elements that were not assigned (badges, leaderboard, points) are, yet, among the most commonly used in gamification [Subhash and Cudney, 2018]. This can be explained by the majority of neutral (for badges) or negative influences exhibited by these game elements in the study used to build our model. We decided to prioritize the situational and contextual levels of motivation over general preferences that we observed in other studies [Hallifax et al., 2019a]. We should, however, investigate how general preferences for specific game elements (such as badges, for instance) could be integrated into the algorithm.

Another way of improvement lies in the compromise of each profile. We did a simple compromise where each profile had the same weight. This choice may not be sufficiently appropriate to balance the negative effect on motivation with a positive effect considering the player types. Thus, further studies should be conducted to improve the algorithm and the combination of profiles, attributing weights to different profiles, for instance. We believe that the dual profile adaptation could be even more reinforced by adding more information on the learners. For example, tailoring to personality traits has shown some promise. It would therefore be interesting to study whether changing or adding profiles to the learner model would increase the effectiveness of the adaptation. However, it is also possible that adding more profiles to the learner model may dilute the differences between learners, making it more difficult to provide accurate recommendations to tailor gamification.

From an **empirical perspective**, this study in real-class settings gives us some insights into the motivational and behavioral outcomes of gamification.

Firstly, we observed two contradictory trends in the different types of motivation (most are decreasing but some are increasing) that were only visible after a certain period of time. We also observed that overall learners' engagement gradually decreased over time, with slight differences according to the different emerging patterns. We, therefore, argue that future studies should be considered only in longer settings so that gamification mechanisms have time to properly impact learner motivation and engagement. In addition, the differences observed in each type of motivation reinforce the idea that motivation should be considered with a multi-dimensional approach to achieve a better understanding of gamification.

The overall decrease in engagement and motivation can be explained by two main reasons: the increasing complexity of the learning content and the lack of novelty or weariness effect. The first reason could cause more marked effects on motivation and a loss of engagement during the second period of the study, which covered more complex concepts. In their study on engagement, O'Brien and Toms [2008] identify task difficulty as a potential factor of disengagement. Landers et al. [2017] showed that their gamification had a positive impact on learners until task difficulty became too great. This seems to suggest that gamification, even when adapted, cannot overcome the effects caused by the underlying learning content. Regarding the second reason, several studies discuss how a novelty effect could lead to positive effects of gamification that would not necessarily continue over time [Seaborn and Fels, 2015a; Hamari et al., 2014; Koivisto and Hamari, 2019]. This novelty effect is often raised in gamification studies [Hamari et al., 2014; Hallifax et al., 2019b] as a reason why shorter studies fail to show the more complex results that can be observed in longer studies.

Several longitudinal studies corroborate that gamification suffers from the novelty effect [Sanchez et al., 2020; Rodrigues et al., 2022a]. It is also possible that the students felt a certain weariness towards the platform content (lack of variety in quiz format and content). This is in line with the study of O'Brien and Toms [2008] which identifies the lack of novelty as a potential factor of disengagement. This would imply that gamification could not compensate for these detrimental effects on motivation and engagement, which are due to the nature of the learning activity itself.

Secondly, it appears that tailoring gamification to users' profiles did not have the same effects on motivation as on engagement.

Regarding motivation, we did not observe any significant differences between adapted or non-adapted conditions. We, however, observed a tendency to obtain more pronounced effects with tailored gamification. This result echoes those of the study conducted by Oliveira et al. [2022a] who find no main effects on students' perceived flow between personalized and non-personalized gamification. They suggest that personalizing game elements according to the dominant gamer type profile may not be enough to improve user experience. We showed in this study that even taking into account a more complete profile to adapt the game elements, and not only the dominant player type, is not enough to improve learner motivation. As I already mentioned from the design perspective, we have to investigate different ways to improve the combination of profiles for game elements recommendation.

Regarding engagement, in contrast, tailoring game elements seems to have mitigated the loss of engagement, at least on two out of the three emerging behavioral patterns. Adapting the game elements to learners seemed to reduce the decrease of engagement or make it more stable. These results point to the need to observe engagement in its evolution and not only at the end of the experiment like most studies do. This also shows that adapting gamification can make a difference over a long time and argues for long-term studies when analyzing the impact of adapted gamification on learners' engagement. This is in line with Altmeyer et al. [2021b], who showed more significant differences at the end of their study than at the beginning between adapted and non-adapted conditions. Oliveira et al. [2022b] also argue for more empirical and longitudinal studies.

Finally, from the **methodological perspective**, we can derive some **methodological recommendations** from these results. In particular, even if using simulation techniques on data sets seems relevant to evaluate algorithms, they are not sufficient. Studies in ecological contexts are also necessary to observe the effects and the relevance of adaptation on motivational and behavioral outcomes. Finally, we provide insights into how motivation could be studied (with a multi-dimensional approach) and how engagement could be tracked and evaluated using a more granular approach. In particular, we proposed a method to analyze learners' engagement over time using a statistical approach combined with a temporal analysis. We had the chance to use this approach on the datasets of the two large-scale ecological experiments, published in Lavoué et al. [2021] and in Serna et al. [2023]. We showed some similar behavioral patterns between the two studies, reinforcing the reliability of the approach.

In conclusion, our results show that tailored gamification is still a young field of research. Although the results are mixed, there are promising avenues for future exploration. In particular, we believe that our latest analysis on engagement over time represents a significant first step toward the dynamic adaptation and automation of gamification. This is a crucial challenge for future research in tailored gamification and, more broadly, for creating meaningful and positive user experiences.

8. Perspectives

During my work, I explored how interactive systems should be designed to support users in their activities, creating meaningful and adapted experiences that foster motivation and sustained engagement. In particular, I was interested in investigating the properties, functionalities, and affordances grounded on psychological theories that support these experiences. I have studied technology affordances in multi-surface, immersive, and gamified environments. My work is structured around three main research axes which I conduct independently or by combining them. Axis 1) observing and understanding users' activities and experiences with technology to inform the design, conducting situated studies that lead primarily to empirical contributions and design recommendations, and defining behavioral analysis methods that result in methodological contributions; Axis 2) modeling users' characteristics, activities and experience, grounded in theories and relying on empirical findings, which provides methodological contributions; Axis 3) designing tailored or adaptive interactive systems, resulting in technical and design contributions with prototypes of affordances and algorithms development.

Recently, I have developed an interest in hybrid environments, combining digital and physical spaces, which raise new challenges for UX that I detail in section 8.1. Accordingly, I outline my research perspectives in response to these challenges by proposing research avenues for 1) supporting meaningful experience (section 8.2); and 2) supporting sustained engagement by improving adapted experience (section 8.3).

8.1. Toward Hybrid Environments

Hybrid is a general term literally meaning *something made by combining two different elements*. The notion of hybrid environments has, therefore, given rise to a wide variety of definitions and dimensions.

The first key aspect is related to the combination of physical and digital information. [Rekimoto and Saitoh, 1999] proposed augmenting the environment to create a spatially continuous workspace for hybrid computing environments, in which users can smoothly interchange digital information among various devices and physical objects. From there, various works consider hybrid environments as the combination of heterogeneous devices, and mostly different displays. Switching from one device to another for both individual or collective activities raises issues related to the discontinuity of interaction and disruptive changes of context. Perelman et al. [2022], for instance, propose tackling this challenge by investigating visual transitions between devices. The combination of devices also applies to immersive environments. For instance, Cavallo et al. [2019] propose a configurable hybrid immersive environment, combining heterogeneous technologies (AR, VR, mobile devices, and robotic arms). They propose novel interaction methodologies to couple the physical environment with AR and VR technologies, enabling the visualization of complex types of data in collaborative settings.

A second key aspect of hybrid environment is the notion of distance, particularly in CSCW and CSCL research fields. According to Duckert et al. [2023], a hybrid environment is characterized by the spatial distance separating the members of a group. They define hybrid work "*as situations where at least three actors are located at fewer geographical sites than the number of actors (but not all collocated), and all actors are mutually dependent in their work*". Considering discontinuities as gaps or a lack of coherence in aspects of work [Watson-Manheim et al., 2002], they identify discontinuities in terms of communication and group coordination. They propose to tackle these with two main design challenges for hybrid work technologies: the increased complexities involved in 1) creating common ground, and 2) balancing sub-group dynamics in hybrid work. Finally they propose a new specific challenge, called the *collocated distance*, "*to explore the collocated boundaries which exist in a hybrid setup and use these collocated boundaries as a design characteristic for hybrid technologies*".

In CSCL, research has shown that alternating between presence and distance also creates discontinuity in terms of motivation. It is not always easy to make links between various learning environments (physical and digital) and to see the complementarity between these different times, spaces, and tools. This is underlined by a recent study on distance learning by Molinari and Schneider [2020], who point out, among other things, that students find it difficult to set up an appropriate workspace, remain motivated over time, keep track of their progress, and reward themselves for their efforts.

Finally, all these considerations regarding hybrid environments underline a key aspect related to the social dimension. de Souza e Silva [2006], who investigate the use of mobile technologies to augment the environment, argue that hybrid spaces are mobile and social. "*A hybrid space is a conceptual space created by the merging of borders between physical and digital spaces, because of the use of mobile technologies as social devices. Nevertheless, a hybrid space is not constructed by technology. It is built by the connection of mobility and communication and materialized by social networks developed simultaneously in physical and digital spaces*". This is in line with the work of Hornecker and Buur [2006], in which the authors underline that hybrid environments are inherently "socially-organized settings." In a recent study on location-based games, Xu et al. [2023] showed that new social dynamics occurred in the hybrid space. They observed that spontaneously formed leadership roles and mentor-mentee relationships supported autonomy among players in the hybrid space. They also underline challenges related to the need for in-game communication features to remove barriers between in-person and remote gamers and facilitate players' coordination and collaboration.

In summary, hybrid environments create opportunities for the completion of complex tasks and social interactions but also raise several challenges related to discontinuities in terms of interaction, motivation, communication, awareness, and the coordination of sub-group dynamics or in-person/remote group members. In the following sections, I will develop some research avenues to tackle these challenges by offering sustained engagement and motivation

8.2. Supporting meaningful experience in Hybrid Environments

Supporting meaningful experience in hybrid environments implies designing technology that can address the various discontinuities identified previously. To inform the design of such technology, I plan to continue investigating the impact of design choices on users'

experiences and behaviors. This will contribute to better understand the relation between the different dimensions of user experience (Research Axis 1) and to propose design methods to guide the design of relevant affordances (Research Axis 3). I present here three avenues that I have begun to explore in ongoing projects, new collaborations, or submitted projects. These avenues are: 1) analysing the relation between collaboration and user experience; 2) investigating hybrid gamification; and 3) investigating immersive affordances.

8.2.1. Analysing the relation between collaboration and user experience

As mentioned previously, hybrid environments may favor social interaction and support collaboration. In my previous work presented in chapter 3, we demonstrated that even if collaboration mechanisms can be analyzed as standalone behaviors, they should be considered as consequential behaviors. We also highlighted some challenges in designing relevant affordances for awareness, regulation and information sharing. I am thus particularly interested in extending my research on analyzing collaborative mechanisms in hybrid environments and their relationships with other aspects of user experience (engagement, immersion and motivation).

Collaboration, immersion and engagement

Considering discontinuities in terms of communication and coordination brought by the hybrid aspects, I believe that research should be conducted to better understand the relationships between these collaborative mechanisms and various dimensions of user experience.For instance, according to Oh et al. [2018], the effectiveness of communication is correlated with immersion, and more specifically with a good level of social presence. Several studies have shown that social presence could have an impact on different factors such as users' participation and satisfaction [Zhao et al., 2014; Richardson et al., 2017]. In Basille et al. [2022], presented in chapter 4, we began investigating the impact of technology affordances on social presence and on collaborative mechanisms. We observed potential influences of social presence on collaboration, especially for information sharing. We also highlighted the need to consolidate our analysis methods to better characterize the relationship between the different concepts. In particular, I believe that more automated and in depth analysis of discussions could enrich the understanding of collaboration and engagement. For instance, there are promising methods using machine learning and Natural Language Processing techniques, including the use of text data from chat logs, discussion forums, and other online platforms to identify patterns of behavior, such as engagement or participation [Jamsandekar et al., 2024]. This also aligns with the recent trends in analyzing collaboration from multiple group data sources as done in collaboration analytics [Schneider et al., 2021; Martinez-Maldonado et al., 2021] or combining behavioral analysis to other sources of data as done when analyzing regulation [Järvelä et al., 2016, 2021].

In a short-term perspective, we are currently working on these issues through a collaboration with researchers in language science from the ICAR laboratory (BODEGA project co-coordinated with Matthieu Quignard). This collaboration takes the form of a multidisciplinary approach combining an analysis of social interactions, conversation analysis (from a language science perspective) and engagement. In particular, in Anthony Basille 's PhD, we aim to explore the combination of learning analytics approaches with other methods derived from the conversational analysis domain to overcome the lack of information on

collaborative processes from logs to inform about learner engagement and collaboration. We jointly improved a collaborative game (from results of the study described in Chapter 4) and designed an experimental protocol with different communication modalities. We collected data from 8 groups of 3 participants for each modality leading to a sample of 72 participants. From an empirical perspective, we are currently studying to what extent the different communication modalities impact social presence and regulation processes to determine if there is a correlation between the two dimensions.

From a methodological perspective, we are currently working on several aspects that should contribute to more efficient methods to study collaboration using multimodal data. First, we are improving our approach to observe collaboration from video analysis. We have proposed a new analysis grid combining our top-down approach driven by theory (using the grid proposed in Lili Tong's PhD) and ICAR bottom-up approach (using micro observations related to conversational analysis). This enables us to enrich our grid with indicators linked to the analysis of discussions and indicators on emotional and social aspects. However, applying such a grid to an entire corpus is a very time-consuming task. One avenue of research is to propose reliable methods of automatic annotation. We are currently investigating how to apply our analysis grid using machine learning techniques. Another research avenue lies in investigating how to combine the data from audio or video annotation with data logs to identify behavioral patterns and to study their dynamic transitions during the activity, such as using Markov models.

Collaboration and motivation

I am also interested in better characterizing the relationship between motivation and collaboration to offer relevant affordances to overcome motivational discontinuities. In CSCL some researchers have started to investigate the significance of motivation in collaborative learning. Järvelä et al. [2010] argue that research on motivation should combine the study of individual and social processes. They underline several challenges, such as how to study the social processes of motivation in dynamic, socially challenging collaborative learning activities, or how motivation can be operationalized and investigated as a combined individual–social phenomenon. Recently, Järvenoja et al. [2020] investigated how the support for motivation regulation could increase regulation processes within a group. They observed that collaborative regulation of motivation was infrequent among group members. Based on their observations, they developed a tool to support regulation of motivation and emotions within groups. These works open up promising avenues of research to meet the challenges raised by hybrid environments.

In particular, in collaborative situations such as student projects, users must be motivated to interact and carry out tasks together, sometimes over a long period and with potential fluctuations of temporal and spatial dimensions, creating different dynamics within the group. The difficulty of perceiving the complementarity between these different dynamics and digital environments can affect motivation. I am therefore interested in exploring how to design motivational affordances to sustain both individual and collective motivations to address these motivational discontinuities.

To address this research avenue, we recently started to collaborate with researchers from the LISN laboratory (Jean-Claude Martin), CERAG laboratory (Agnes Helme-Guizon) and

CIAMS laboratory (Alexandra Perrot). We aim to establish a common multidisciplinary conceptual framework for characterizing motivation within a group, including collective self-determination, inter-individual differences, and their evolution over time. This framework would serve as a basis to specify a unified architecture containing computational context and user models. We plan to explore how to integrate individual characteristics and those of the group, identifying stable and dynamic dimensions (subgroup configuration, engaged behaviors) to propose adaptation mechanisms to ensure motivational continuity across different spaces and times, hybrid devices and group composition.

8.2.2. Investigating hybrid gamification

Classical approaches to support motivation, such as gamification, are usually designed for a given context and are not well adapted to support students with breaks in space and time. Some works inspired by tangible interfaces and data physicalization are emerging and aim to fill the gap between these different spaces. Physical objects, which can provide a link with digital space, are based on the principles of tangible interaction, which according to Hornecker and Buur [2006] encompasses a wide range of systems and interfaces based on embodied interaction [Marshall and Hornecker, 2013], tangible manipulation and the physical representation of data (also known as physicalization [Stusak et al., 2014; Jansen et al., 2015]). Tangible interfaces are anchored in real space and enable physical spaces to be digitally augmented. In the educational context, for instance, the work of Sadka et al. [2018] focuses on the social aspects of motivation and the continuity of awareness thanks to a mechanical object that accompanies parents' reflection on their role during interaction with their child. Molinari and Schneider [2020] propose a toolbox of tangible objects to support self-regulation mechanisms and volitional strategies for distance learners. Thanks to their affordances, these tangible objects enable active manipulation, with a higher level of engagement and a facilitated social dimension.

In the field of gamification, some researchers have started to investigate physicality. For instance, Altmeyer et al. [2021a] explored transforming virtual gamification elements (such as points or leaderboards) to their physical counterparts and showed that physical gamification was perceived as significantly more persuasive and more meaningful than their virtual counterparts. However, the design of such objects still raises many questions and provides numerous directions to explore, in particular on data acquisition, visualization, and interaction with these tangible artifacts. There is also a lack of empirical evidence on the effects of such hybrid gamification.

Design space and first explorations

In a collaboration with researchers in neurosciences of HESPER laboratory (Stephanie Mazza) and CRNL (Amandine Rey, Karine Spiegel), we explore how to support teenagers in acquiring good sleep behaviors (Ludisom project). To maintain their motivation, we developed a gamified digital platform. However we identified some limitations in the approach, raising challenges that we would like to address through the exlporation of physicalization of motivational data. Indeed, adolescents can only consult motivational elements when they are connected to the platform, whereas they need to anchor their behaviour change in their daily lives, outside the periods of connection to the platform, creating discontinuity of motivation. Secondly, one of the aims of the project is to raise awareness of the need to reduce their use

of screens. Thus, we suggest that physical objects would allow a connection between the digital and physical environments, supporting the continuity of motivation [Lavoue et al., 2021].

We also proposed to structure the reflection around the design of such objects by introducing a design space with Anagaël Perreira, a student from the Dimplôme Supérieur d'Arts Appliqués (DSAA) of Villefontaine [Serna et al., 2021]. We defined three dimensions of motivation (spatial, temporal, and social) and seven properties to consider in order to design objects that ensure the continuity of motivation. Figure 8.1 illustrates an example of the properties explored for a motivational strategy focused on progression. This work has led to the creation of a kit for running co-design workshops and a kit that teachers can use to design their own objects.

These objects and tools have not yet been tested in real-world situations. One avenue for my future work is therefore to investigate the design of such objects (including considering how to update them over time) and to conduct studies to gather empirical data on the effects of these objects on motivation and engagement. In particular, I am interested in investigating situated motivational affordances that address spatial discontinuities, creating links between various spaces (such as the classroom and home in the educational context).

Hybrid gamification for therapeutic patient education

To continue exploring tangible gamification for education, health, and well-being, we have begun a collaboration with researchers at the LCOMS laboratory (David Bertolo, Isabelle Pecci) and the PERSEUS laboratory (Stéphanie Fleck), who are working on tangible interfaces in education. We have obtained ANR funding for a project, THERAPEUTIC, which aims to develop gamified, incentivizing tangible interfaces for Therapeutic Patient Education (TPE), applied to osteoporosis for elderly people.

In this project, we aim to explore the design of meaningful hybrid gamification to support elderly people in maintaining their persistence in the behavioral changes required in their daily lives. Recent systematic reviews of literature have shown that gamification can support behavior changes in the health domain [Orji et al., 2017b; Orji and Moffatt, 2018]. Koivisto and Malik [2021] argue for the potential of gamification for older adults in their literature review, especially in health-related contexts. Martinho et al. [2020] observed that the use of gamification techniques to support elderly people was beneficial in improving well-being as well as their physical, cognitive, social, and emotional states. From a general perspective, the results of these studies tend to show positive effects of gamification. However, Koivisto and Malik [2021] insist on the need for a better understanding of the underlying motivations, challenges, and design solutions required for older adults due to their varying needs, and physical and psychological characteristics. Few studies investigate seniors' game preferences, such as those by [Altmeyer et al., 2018; Birk et al., 2017; Kappen et al., 2016]. For instance, Altmeyer et al. [2018] showed that seniors' main motivation to play was socializing, but specific game elements were considered meaningless or a source of pressure.

Since the effects of gamification are highly dependent on specific contexts, which vary across individuals, a challenge lies in the deep understanding and modeling of all dimensions of motivation and game preferences of older adults in the context of improving well-being related to TPE. This understanding is crucial to implement meaningful and tailored gamification. In the project, LIRIS will be responsible for identifying motivational strategies for elderly patients, integrating hybrid tailored gamification in the hybrid environment, and

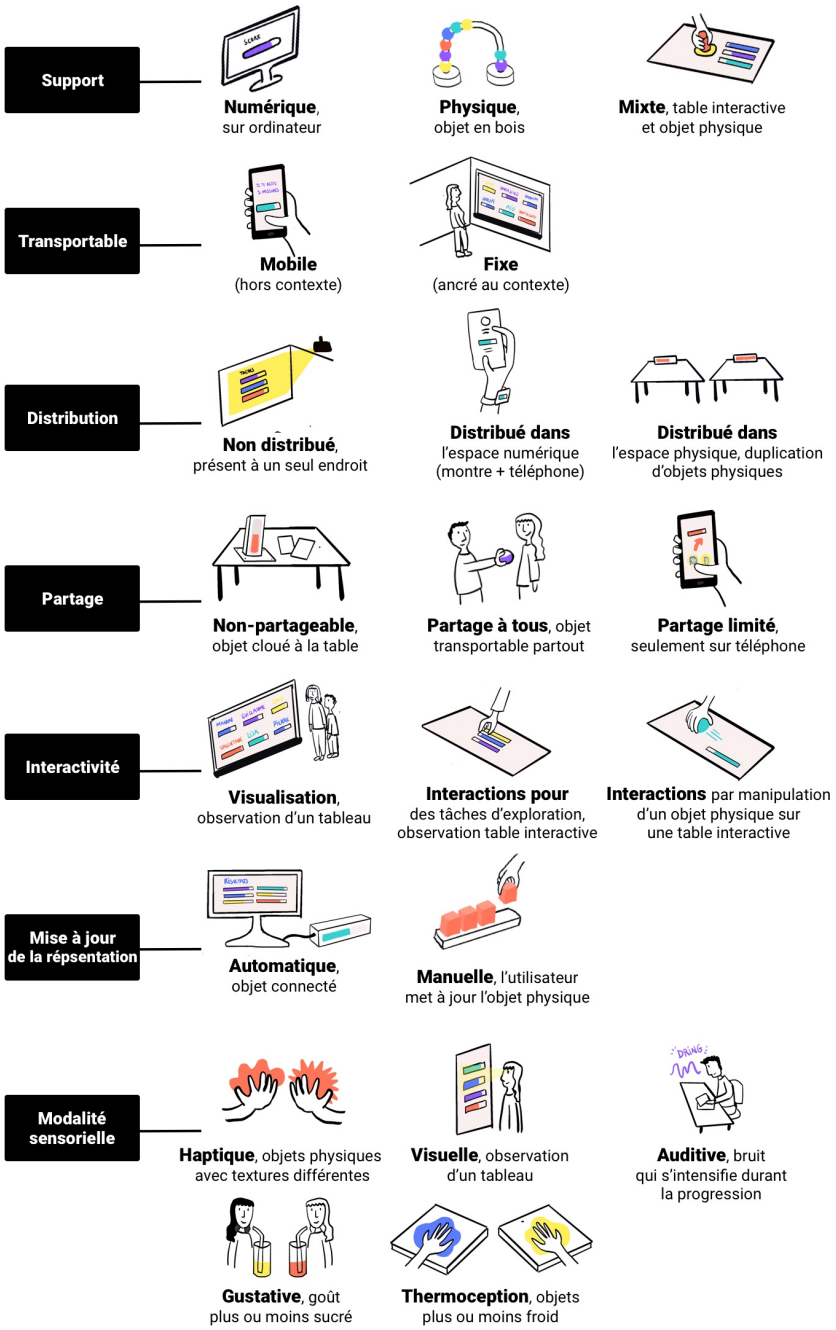


Figure 8.1.: Exploration of the seven properties of the design space for the progression motivational strategy, published in [Serna et al., 2021].

evaluating its impact on patient engagement in the long term. The aims are to develop tools to support behavioral changes from a long-term perspective, fostering motivation across different spaces (considering the alternation of TPE sessions at the hospital and home) and the tangibilization of the TPE environment. In particular, we want to develop different artifacts combining digital and tangible properties in collaboration with LCOMS (exploring the feasibility in terms of activity tracking, updating game elements, and visualization capabilities).

8.2.3. Investigating immersive affordances on user experience

As underlined in the theoretical foundations, the concept of immersion can refer both to the characteristics, features, or properties of the technology and to the psychological state of an individual, which can be considered part of the perceived experience. We showed in Chapter4 that certain design choices can influence the perceived sense of presence or flow, concepts considered to be close to cognitive immersion. I would like to continue addressing this challenge by better understanding how technology affordances influence perceptions of UX (including immersion, flow, presence, engagement, and motivation) to inform the design of such technology. Considering the hybridization of immersive learning environments, I am interested in exploring the balance between immersive features and the integration of elements from the physical world that may improve (or not) the overall experience.

In particular, some researchers, such as Roussou and Slater [2020], underline that VR learning environments should be coupled with support for reflection to improve their efficiency. Reflection is defined as the ability to reflect on thoughts, actions, and experiences to promote self-awareness and continuous improvement [Schön, 1983]. This metacognitive process can occur during the action (*reflection-in-action*) or after (*reflection-on-action*). Supporting reflection can lead to hybrid environments combining different aspects, such as temporal (distinguishing between during and after the activity) and spatial (digital or physical environments). In HCI, several works have investigated how to support reflection [Baumer et al., 2014], proposing, for instance design patterns [Bentvelzen et al., 2022]. However, supporting reflection during the action could seem contrary to cognitive immersion. Researchers highlight that technological features (such as gamification or immersion) are usually considered an obstacle to reflection as underlined by Khaled [2018]. To tackle this challenge, Tang et al. [2023] investigate how providing feedback using gamification impacts user experience in VR. Their results show that gamification improved player experience and encouraged players to reflect on goal achievement and performance, but diverted their attention from nuances in the task. These results seem promising and open interesting avenues for research. It would be interesting to propose a design space for reflection affordances in immersive hybrid environments that would cover the different temporal and spatial dimensions related to reflection. It would be also interesting to systematize the evaluation of the impact of such affordances on user experience, including presence, flow, cognitive load and other relevant aspects of the experience.

We investigate that question in the ANR RENFORCE, coordinated by Elise Lavoué and involving several academic partners (ORIGAMI LIRIS, INL and ECP). The project is dedicated to developing a Reflexive Multisensory Immersive Environment for Chemical Risk Training. In the project, we rely on the theoretical framework proposed by Schön [1983] to propose an immersive experience embedded in a more extended learning process, including self-reflection processes during and after the experience. This approach is intended to help learners become aware of and formalize knowledge derived from their experiences. With

the co-supervision of a PhD student (Valentin Midez, who started is PhD in December 2023), we aim to propose a method to analyze and visualize physiological and behavioral data to support learners' reflexive processes, both during and after the VR experience in a debriefing environment, creating an hybrid experience. Throughout this task, we will evaluate four aspects: 1) the relevance and usability of the visual indicators, 2) the cognitive load, presence and immersion perceived during the VR session, 3) the gain in procedural knowledge and 4) the relevance of the learners' behaviors compared to behavioral skills to be acquired.

In addition to the objectives defined in the project, I would like to explore hybrid configurations to improve reflection during the immersive experience, allowing a trainer to interact directly with the learner. Recent work in hybrid environments has underlined the creation of spontaneous mentor-mentee relationships [Xu et al., 2023]. Additionally, some studies (mostly in medical or surgical training) have shown that the presence of a teacher or an expert during the experience has positive effects on learning, reducing learners' cognitive load and helping learners integrate declarative knowledge with physical skills [Cecilio-Fernandes et al., 2020; Ojala et al., 2022]. Ghamandi et al. [2024] developed a remote, synchronous, asymmetric VR collaborative task to identify the combinations of communication modalities that provide the most efficient transfer of information in mentor-mentee collaborative settings. Relying on these recent studies, it would thus be interesting to investigate interactions techniques or communication modalities to improve the reflection-in-action with expert feedback during the immersive experience. This could be explored with a PhD funded by the PePr Ensemble.

8.3. Supporting sustained engagement by improving adapted experience in Hybrid Environments

Hybrid environments raise challenges related to the changing of spaces, the reconfiguration of groups, and varying times. Considering that engagement and experiences are highly situational, personal, and vary both within and across individuals over time [Perski et al., 2017], there is a necessity to design technology that can adapt to these specific features. In the context of educational technology research, the same challenges are raised. For instance, Romero et al. [2024] argue that *the exploration of affordances, learning analytics, and dynamic adaptation mechanisms represents a crucial frontier*. In the health domain, researchers also highlight challenges in designing complex adaptive systems [Blandford, 2019]. The tailoring approach we have proposed is promising and opens interesting avenues for research into the capitalization of results and generalization of models and tools. Our results also open perspectives for dynamic adaptation methods based on tracking and identifying behavior during the experience.

In addition, there are challenges related to the values and properties that should be integrated into intelligent systems from a user perspective [Cockton, 2004; Friedman et al., 2017]. To empower people to use systems that integrate adaptive capacities or automation through algorithmic decision-making, Abdul et al. [2018] argue that *people should be able to understand how the technology may affect them, trust it, and feel in control*. They define challenges related to explainable, accountable, and intelligible systems. In several domains, researchers have identified these properties as fundamental to technology acceptance and user engagement, such as Blandford [2019] for health, or Oinas-Kukkonen and Harjumaa [2009] who define design principles related to system credibility for persuasive technologies.

Thus, I would like to continue investigating how to model users' characteristics, activities, and experiences (Research Axis 2) and develop tools to automate the design of tailored technologies and algorithms to provide adaptive systems (Research Axis 3). Additionally, I would like to investigate how to improve adapted experiences with other approaches, such as recommender systems or design methods centered on values (Research Axis 3).

8.3.1. Improving tailoring approach and user models

To tailor gamification to users' characteristics, we proposed a user model relying on a statistical approach, computing the positive and negative influences of game elements on motivational and behavioral outcomes. The model, presented in Chapter 6, integrates these influences to account for complex multi-dimensional profiles (player profile and initial motivation). We then developed an algorithm, presented in Chapter 7, to combine these multi-dimensional profiles and recommend a specific game element to each learner. As underlined in the discussion of both chapters, there are some research avenues to improve the modeling approach and the recommendation algorithm.

First, some work should be conducted to integrate a more generic approach. We decided to prioritize the situational levels of motivation (here for learning mathematics), since our previous work showed the importance of context on the perception of game elements [Hallifax et al., 2019a], corroborated by the literature on motivation. However, it seems worthwhile to propose models for other subjects or even for other domains (for instance, for health), generalizing some parts of the model. I have identified two ways of achieving this objective: conducting more studies comparing the effects of game elements for different subjects to identify patterns of influences following common trends, and exploring the integration of more generic recommendations from the existing literature or from the Hexad framework.

Second, the recommendation algorithm can be improved by investigating different ways to compromise between profiles. In the Ludimoodle+ project, which is the continuation of the Ludimoodle project, we are currently working with Nihal Ouherrou (a post-doctoral student co-supervised with Elise Lavoué), on the development of an improved version of the algorithm to better consider the complexity of motivation.

Another way of improving the algorithm would be to investigate the use of additional information on users, such as more objective measures than motivation, which can only be measured with questionnaires and thus is difficult to assess continuously (from the dynamic adaptation perspective). In particular, behavioral outcomes could be considered to specify correlations between game elements and users' characteristics to enrich user models, as done in [Barata et al., 2017; Hassan et al., 2021]. It would therefore be interesting to study whether changing or adding profiles to the learner model would increase the relevance of the recommendation. However, it is also possible that adding more profiles to the learner model may dilute the differences between learners, making it more difficult to provide accurate recommendations to tailor gamification. More studies on the evaluation of the impact of tailored approaches should be conducted. In Ludimoodle+, we are currently conducting a large field study with 72 classes, i.e., around 1900 learners, divided into 3 experimental conditions (without gamification, with randomly assigned game elements, and tailored game elements) to evaluate the impact of tailored gamification on motivation and performance.

Third, I believe that there is an important work to conduct to propose robust methods and tools to assist the design of tailored gamification, particularly by providing efficient ways to

support design decisions. In their recent work, Rodrigues et al. [2022b] argue that tools for automating gamification personalization are needed to select the relevant users' characteristics and to propose personalized gamification designs. They propose conditional decision trees that synthesize users' opinions on the game elements they consider the most useful for different learning activity types, and they implemented a recommender system that suggests game elements to use. As underlined in the discussion of Chapter 5, I would like to improve the design space and tools proposed in [Hallifax et al., 2018] with more examples and inspiration boards, and to conduct more formal studies to test their expressivity and efficiency. This would tackle challenges underlined in research on collaborative design ideation regarding the need for more evaluation of tool efficacy [Peters and Calvo, 2021] and the need to provide support for inspiration [Halskov and Dalsgård, 2006].

8.3.2. Tackling dynamic aspects of experience

As we discussed previously, our work on the analysis of engagement over time (presented in Chapter 5 and published in [Serna et al., 2023]) is a first step toward the dynamic adaptation of gamification and its automation, which is an important challenge for future research [Bennani et al., 2021; Oliveira et al., 2022b]. In their systematic literature review, Bennani et al. [2021] outline several challenges of adaptive gamification approaches, including the dynamic detection and analysis of learners' implicit information to adapt the gamification process based on the player type, preferences, interactions, motivation, and feedback. They also emphasize the importance of applying theories and algorithms of Artificial Intelligence (AI) to implement systems able to learn from the users' different experiences and adapt to different learning situations.

A few works have started to investigate how to adapt to learners' interactions. For instance, Paiva et al. [2016] proposed a model of interactions, called the student's interactional profile, based on data collected from students' interactions with the educational resources available in the studied environment. They only used data to visualize students' interactions to assist pedagogical decision-making. Knutas et al. [2017, 2018] defined a user model based on the player profile but also on users' interaction with the system. Finally, Hassan et al. [2021] proposed to adapt both game elements and learning activities using an adaptation engine based on interactions. They distinguish three types of interactions (collaborative, gamification, and content interactions) that are associated with different learning styles. For each learner, they calculate their learning dimensions using the interaction category and the time taken to perform the activity. According to the calculated profile, they assign the corresponding game element and activity. In parallel, in a broader context, Romero et al. [2024] underlined the capacity of learning analytics to support dynamic and adaptive game-based learning environments. In their literature review on the use of Learning Analytics (LA), Banihashem et al. [2023] identified classification, regression, clustering, support vector machines, and decision tree methods as the most used methods to track user performance during the activity, to provide intelligent feedback, and to detect and cluster users based on their performance and activities. For instance, Ruipérez-Valiente et al. [2017] proposed to analyze the relationship among students' intention, concentration, and efficiency for the achievement of badges with other typical indicators of students' performance and behavior. They applied clustering methods to find different behavioral profiles that can then be used to adapt the learning experiences of students.

Considering these very recent works, I believe that there is an interesting avenue to improve our initial results on the analysis of engagement over time. Combining these results with

the mentioned approaches should allow us to enhance engagement detection and trigger adaptation mechanisms. There is also a need to conduct studies to empirically assess the impact of such mechanisms on user experience, motivation, and engagement. We plan to explore precisely these research avenues in the ANR THERAPEUTIC project, as we aim to support behavior change over time by adapting game elements according to patients' engaged behaviors.

8.3.3. Combining approaches to improve adapted experience

Combining recommender systems and tailored gamification

Supporting well-being and human flourishing can be promoted by encouraging healthy behaviors or discouraging risky behaviors. As underlined by Blandford [2019], challenges of HCI applied to health include opportunities to *empower people to manage their health and well-being in ways that better fit their lives and values*. The author also highlights the need for personal health technologies, extending HCI techniques to design for complex adaptive systems.

To properly incorporate behavior change models and theories, a system should provide a combination of services, including suggestions or recommendations, progress tracking and support for individuals, and be adjusted over time based on the user's progress [Torkamaan and Ziegler, 2021]. These aspects are often explored through persuasive strategies such as self-monitoring, praise, tailoring and personalization, suggestions and recommendations to motivate behavior changes [Fogg, 2002; Oinas-Kukkonen and Harjumaa, 2009]. Various recent studies have shown that persuasive games and gamified systems can enhance users' motivation and engagement for behavior change [Orji et al., 2017b]. A recent study by Villalobos-Zúñiga and Cherubini [2020] proposes a taxonomy for behavior change applications based on SDT [Ryan and Deci, 2000b]. The authors argue that future research should focus on tailoring system interventions to resonate with the constructs of SDT, in particular by offering optimal challenges to users. In the same line, Oyebode et al. [2021] highlight several design recommendations such as tailoring the content and allowing users to set their own goals, offering suggestions on both how to set effective goals and how to reach them. Our approach based on tailored gamification could tackle some of these challenges, including the design of tailored motivational affordances and the dynamic tracking of engaged behavioral patterns. However, this approach should be combined with other approaches to reinforce persuasion. For instance, recommender systems can be used to provide users with personalized content and could be useful for personalizing optimal challenges. In the field of recommender systems, the works on healthy food recommendations [Chen et al., 2021; Ge et al., 2015; Min et al., 2020] provide promising results, mainly focusing on recommending personalized recipes or diets. However, these works also highlight some limitations, such as ignoring crucial health factors or failing to take into account the motivational aspects of behavior change.

To tackle these challenges, I started a collaboration with Diana Nurbakova (LIRIS-DRIM) thanks to a lab-funded project called APAPS, which stands for Adaptive and Privacy-Aware Persuasive Strategy for behavior change. We explore tailoring persuasion strategies and system recommendations to users' profiles while providing comprehensible user control over their privacy for healthy food promotion. The main objective of the project is to explore the fusion of recommender systems and persuasive and gamified strategies to overcome

the individual limits of each domain and better support users in their behavior change by offering them optimal challenges. We also aim to explore and identify different privacy control levels and their impact on the relevance of the system. For this part of the project, we will work with Antoine Boutet (CITI-PRIVATICS). The objectives of the project were published in a position paper for the "Adaptive and Personalized Persuasive Technologies" workshop held at the UMAP 2023 conference [Nurbakova et al., 2023b]. We also published a first exploration on integrating personalized challenges to extend the idea of a constrained question-answering system over a knowledge graph proposed by Chen et al. [2021], in a workshop on Behavior Change and Persuasive Recommender Systems held at RecSys' 23 [Nurbakova et al., 2023a].

Integrating values in adaptive systems

As underlined previously, there is an important challenge for complex adaptive systems to integrate human values into their design. In particular, adaptation processes should be understandable and controllable by users to create a meaningful and adapted experience. This gives rise to various avenues of research, such as understanding users' values and how to design technology properties that are aligned with these values, or exploring interactive explanations and interfaces for intelligibility as suggested by Abdul et al. [2018]. To address these challenges, some works focus on the concept of AI alignment, which consists of ensuring that an AI produces the desired results without undesirable side effects [Goyal et al., 2024]. Other works propose design recommendations, such as [Amershi et al., 2019], or adopt a values- and ethics-centered design approach [Umbrello and De Bellis, 2018; Varanasi and Goyal, 2023]. All these works underline issues inherent in AI systems: the difficulty of understanding how these systems work for humans and the ability of these systems to integrate values, especially as these values often vary depending on the context or the given situation. Additionally, researchers underline the importance of taking into account user behavior to propose longitudinal alignment [Goyal et al., 2024], with systems capable of adapting over time [Amershi et al., 2019].

In the ANR ACCELER.IA project, we co-supervised the M1 thesis of Marceau Nahon with Aurélien Tabard (LIRIS-SICAL). We started to investigate how to capture users' values in context by adopting a sensitive design approach, which is defined as a theoretically grounded approach to the design of technology that accounts for human values in a principled and systematic manner throughout the design process [Friedman et al., 2017]. We investigated how users' preferences can be captured to incorporate more ethical considerations into the design of automated algorithmic complex decision-making. We proposed a method to measure how much the context can impact the differences between the declared importance of values and decisions made in a given situation. We developed a survey tool that measures the importance of values in either absolute or relative ways by comparing pairs of values in specific situations. We conducted a preliminary study to test our survey tool, which was published in the TEC category at IHM 24 [Nahon et al., 2024]. This first study confirmed that the importance given to values is context-dependent.

This raises several research avenues regarding how intelligent systems integrate alignment mechanisms that are tailored to users' contextual preferences and behaviors. In particular, I would like to explore how to improve human-AI interaction from a longitudinal perspective.

Part III.

Appendix

A. Ludimoodle Game Elements

Points: Each correct answer given by the learners awarded them points (generally 100 points depending on the difficulty of the question). These points were displayed using a sack or chest of gold coins (the points corresponding to a quiz were show using a sack, and those to a lesson using a larger chest). Learners were also shown the maximum number of points they could score for each lesson and quiz. Points generally match the need for competence regarding the SDT [Sailer et al., 2017; Zainuddin et al., 2020a]. As this game element gives learners a clear representation of how well they are doing in the course, and rewards them for performing better, it is generally given to Players [Marczewski, 2015; Klock et al., 2020].

Badges: For each lesson, learners could earn two categories of badges, one based on how many questions they correctly answered in a row, and one based on how much of the lesson they completed. Each of these badges came in a bronze-silver-gold version based on how well learners achieved these goals, in general these badges were awarded if the learners completed respectively 70-85-100% of the quizzes in a lesson. There was also a set of ”medals” for each quiz in the lesson, so that learners could easily identify which quizzes they needed to try again if they wanted to earn gold in each lesson. Badges match the need for competence regarding the SDT [Sailer et al., 2017; Zainuddin et al., 2020a] and they are generally shown to be motivating for all users [Hallifax et al., 2019a] and explicitly for Players [Klock et al., 2020] and Achievers [Marczewski, 2015].

Avatar: The avatar game element showed a goblin-like character that learners could personalise with various clothes and equipment. As the learners progressed in a lesson they could unlock a different set of objects to use (e.g. medieval, fairy tale, pirates). The avatar could be personalised via an inventory menu displayed near the top of the game element. In general, when learners achieved the required 70% in each quiz in a lesson, they could unlock 1 or 2 objects. Avatar matches the need for autonomy regarding the SDT [Sailer et al., 2017; Zainuddin et al., 2020a]. This kind of game element is generally recommended for Free Spirits, as it provides them with a personalised representation of themselves Marczewski [2015]; Klock et al. [2020], and for Disruptors [Klock et al., 2020].

Progress bar: Learners were shown their progress in the quizzes by way of a rocket ship that travelled from earth to various planets. Each correct answer would charge a ”boost” meter that, when filled, would propel the rocket further. When learners achieved a full 100% of correct answers for a lesson, they would arrive at the planet. This game element matches with the need of competence regarding the SDT [Zainuddin et al., 2020a] and should be particularly interesting for Achievers as they have a clear goal Marczewski [2015]. It is also attributed to Players in several studies [Klock et al., 2020] and can appeal to Disruptors [Hallifax et al., 2019a].

Ranking: This game element is a combination between leaderboards and competition as defined in Klock et al. [2020]. Learners were shown their position in a fictional ”race” against other learners. This position was decided based on their answers (i.e. the more questions they answered correctly, the higher they were ranked in the race). Our initial



Figure A.1.: Point game element. Left side: the course view with all exercises; Right side: exercise view.



Figure A.2.: Badge game element. Left side: the course view with all exercises; Right side: exercise view.

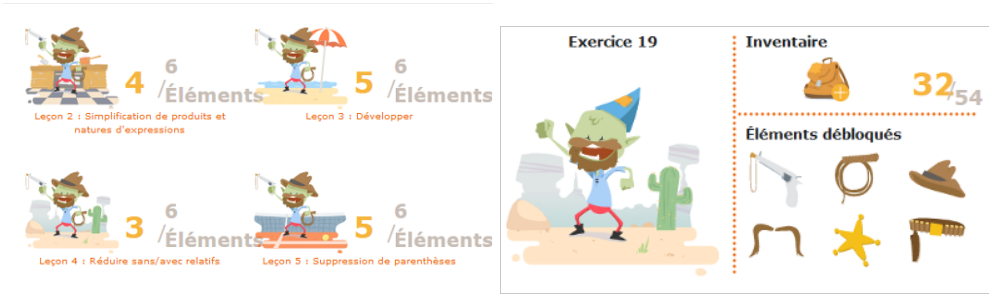


Figure A.3.: Avatar game element. Left side: the course view with all exercises; Right side: exercise view.

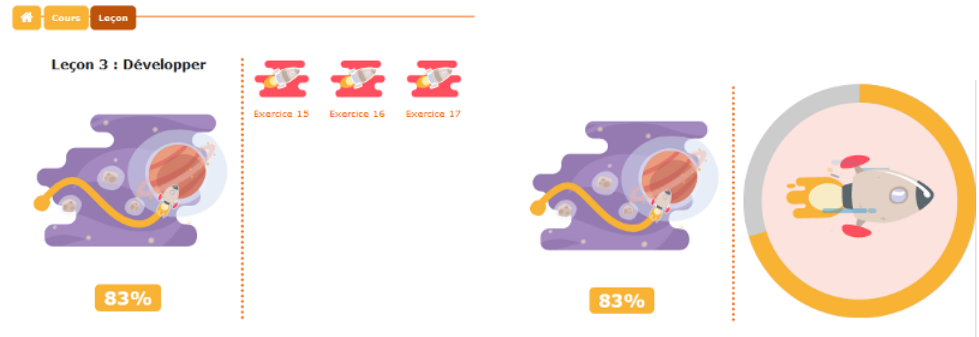


Figure A.4.: Progress game element. Left side: the course view with all exercises; Right side: exercise view.

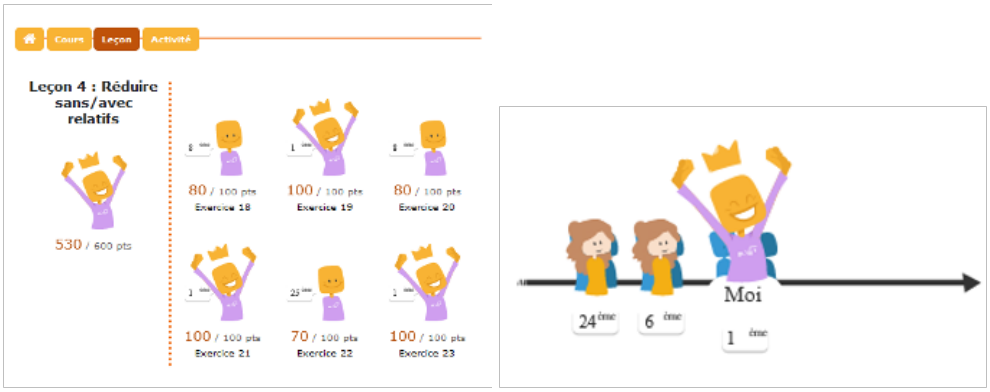


Figure A.5.: Ranking game element. Left side: the course view with all exercises; Right side: exercise view.

idea was to show learners their ranking as compared to their classmates, however teachers explained that they did not want a direct comparison with learners in the same class. We therefore made the compromise to compare the learners to a fictional class, and told them that they were comparing themselves to previous years' attempts (thus still providing a sense of competition). This fictional class was setup so as a few learners scored 100% on all quizzes and all learners were at least in the top half of the ranking. As this game element allows learners to compare themselves to others (even if fictional), it should be motivating for Socialisers (related to the relatedness need identified in the SDT [Zainuddin et al., 2020a]) and Players Marczewski [2015]. Hallifax et al. Hallifax et al. [2019a] showed that compared progress (i.e. leaderboard, ranking etc.) presents positive influences for the Disruptor player type. The meta-analysis conducted by Klock et al. [2020] shows that Socialiser, Player and Disruptor are also the most indicated user types for this kind of game element.

Timer: This game element showed a timer for each quiz. Each of the questions was timed and recorded. Learners were shown the average time taken to answer to previous questions and each time they beat this "reference time" a small maths related character ran faster and faster. Learners were thus encouraged to make their character as fast as possible by answering quickly to questions. They were only rewarded for correct answers, as an incorrect answer would not affect the reference time or the animated character. With this functioning,

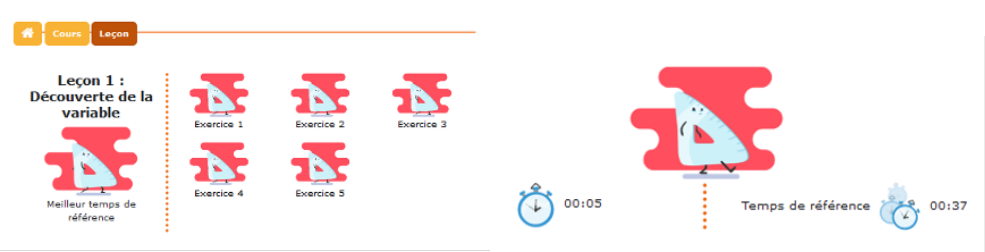


Figure A.6.: Timer game element. Left side: the course view with all exercises; Right side: exercise view.

learners are challenged to beat themselves in a race (matching the competence need related to the SDT), meaning that Achievers and Disruptors would be interested in this activity Marczewski [2015].

B. Adaptation Algorithm

Algorithm B.1: Adapatation algorithm for tailored gamification presented in Chapter 7

```
1  Initialisation – Sort both affinity vectors in decreasing order of affinity
2  affVecHex ← sorted Hexad affinity vector
3  affVecMot ← sorted initial Motivation affinity vector
4  These vectors are structured using the following format: [(gameElement,affinity), (gameElement,affinity)...]
5  overlap ← positive overlap between affVecHex & affVecMot
6  This contains a list of all game elements that have a positive affinity in both affVecHex and affVecMot
7  if overlap is not empty then
8      if overlap contains exactly one element then
9          Suggest element in overlap[0]
10     else
11         Add the rankings for each game element in overlap from affVecHex &
             affVecMot;
12         if one game element has smallest combined ranking then
13             Suggest that element
14         else
15             Add the affinities for each game element in overlap from affVecHex &
                 affVecMot; Suggest game element that has highest combined affinity
16 else
17     Add the rankings for each game element from affVecHex & affVecMot;
18     if one game element has smallest combined ranking then
19         Suggest that element
20     else
21         Add the affinities for each game element from affVecHex & affVecMot;
             Suggest game element that has highest combined affinity
```

C. Ranked List of my publications

Articles in international peer-reviewed journals

[RI11] Elise Lavoué, Sophie Villenave, **Audrey Serna**, Clementine Helfenstein-Didier, Patrick Baert & Guillaume Lavoué (2023). « Influence of Scenarios and Player Traits on Flow in Virtual Reality ». IEEE Transactions on Visualization and Computer Graphics.

SJR : Q1, Impact Factor en 2022: 5.2

[RI10] **Audrey Serna**, Stuart Hallifax & Élise Lavoué (2023). « Investigating the Effects of Tailored Gamification on Learners' Engagement over Time in a Learning Environment ». Proceedings of the ACM on Human-Computer Interaction, vol. 7, n°384, pp. 264-288

SJR : Q2, Impact Factor en 2022: 3.74

[RI9] Stéphanie Reyssier, **A. Serna**, S. Hallifax, J. -C. Marty, S. Simonian & E. Lavoué (2023). « How does adaptive gamification impact different types of student motivation over time? ». Interactive Learning Environments, pp. 1-20.

SJR : Q1, Impact Factor en 2022 : 5.4

[RI8] Lachand-Pascal V., Michel C., **Serna, A**. Tabard, A. (2023). Challenges and Opportunities for Multi-Device Management in Classrooms. ACM Transactions on Computer-Human Interaction (TOCHI). vol. 29, n°6, pp. 1073-0516.

SJR : Q1, Impact Factor en 2022: 3.7

[RI7] Reyssier, Stéphanie; Hallifax, Stuart; **Serna, Audrey**; Marty, Jean-Charles; Stephane, Simonian; Lavoué, Elise. (2022). The Impact of Game Elements on Learner Motivation: Influence of Initial Motivation and Player Profile. IEE Transactions on Learning Technologies. vol. 15, n°1, pp. 42-54.

SJR : Q1,Impact Factor en 2022: 4.433

[RI6] Elise Lavoué, Qinjie Ju, Stuart Hallifax & **Audrey Serna** (2021). « Analyzing the relationships between learners' motivation and observable engaged behaviors in a gamified learning environment ». International Journal of Human-Computer Studies.

SJR : Q1,Impact Factor en 2022: 5.4

[RI5] Guillaume Loup, Sébastien George, Iza Marfisi-Schottman, **Audrey Serna**. A Visual Programming Tool to Design Mixed and Virtual Reality Interactions. International Journal of Virtual Reality, IPI Press, 2018, 18 (02), pp.19-29. http://www.ijvr.org/web/search/singleArticle/367

Impact Factor : 0.79

[RI4] Karim Sehaba, **Audrey Serna**. Decoding social situations in adolescents with Asperger through a serious game. AMSE, Journal of the Association for the Advancement of Modelling and Simulation Techniques in Enterprises (Special edition HANDICAP), 2015, 75 (2), pp.234-246.

[RI3] M. Vahdat, S. George, **A. Serna**. Wizard of Oz in Designing a Collaborative Learning Serious Game on Tabletops. International Journal of Information and Education Technology 3(3) pp. 325-329, ISSN 2010-3689. 2013.

[RI2] **Audrey Serna**, Hélène Pigot, Vincent Rialle. Modeling the Progression of Alzheimer's Disease for Cognitive Assistance and Smart homes. User Modeling

and User-Adapted Interaction, Springer Verlag, 2007, 17, pp.415-438. ⟨10.1007/s11257-007-9032-y⟩. ⟨hal-00200918⟩

SJR : Q1, Impact factor en 2022: 3.6

[RI1] **Audrey Serna**, Hélène Pigot, Vincent Rialle. Computational Representation of Alzheimer's Disease Evolution Applied to a Cooking Activity. Studies in Health Technology and Informatics, IOS Press, 2006, 124, pp.587-592. ⟨hal-00200926⟩

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[CI22] Anthony Basille, Élise Lavoué & **Audrey Serna** (2022). « Impact of Viewpoint on Social Presence and Collaborative Processes in a Collaborative Serious Game ». Proceedings of the 14th International Conference on Computer Supported Education, 24 avril 2022, Prague (République Tchèque), pp. 614-621.

ATIEF : B

[CI21] Stuart Hallifax, Elise Lavoué, **Audrey Serna**. To tailor or not to tailor gamification? An analysis of the impact of tailored game elements on learners' behaviours and motivation. 21th International Conference on Artificial Intelligence in Education, Jul 2020, Ifane, Morocco. pp.216-227. ⟨hal-02573200⟩

Core 2020 : A ; (Taux d'acceptation : 26,6%)

[CI20] Stuart Hallifax, Elise Lavoué, **Audrey Serna**, Jean-Charles Marty. Structural Gamification for Adaptation based on Learning Analytics. EARLI, Aug 2019, Aachen, Germany. pp.383. ⟨hal-02147867⟩

[CI19] Stuart Hallifax, **Audrey Serna**, Jean-Charles Marty, Elise Lavoué. Adaptive gamification in education: A literature review of current trends and developments. European Conference on Technology Enhanced Learning (EC-TEL), Sep 2019, Delft, Netherlands. pp.294-307. ⟨hal-02185634⟩

ATIEF : A

[CI18] Stuart Hallifax, **Audrey Serna**, Jean-Charles Marty, Guillaume Lavoué, Elise Lavoué. Factors to Consider for Tailored Gamification. CHI Play, Oct 2019, Barcelona, Spain. pp.559-572. ⟨hal-02185647⟩

Taux d'acceptation : 28% ; PRIX ; Honorable mention

[CI17] Lili Tong, Aurélien Tabard, Sébastien George & **Audrey Serna** (2017). « Horizontal vs. Vertical: How the Orientation of a Large Interactive Surface Impacts Collaboration in Multi-Surface Environments ». 16th IFIP Conference on Human-Computer Interaction (INTERACT), 29 septembre

2017, Mumbai (Inde), pp. 202-222. doi : 10.1007/978-3-319-67687-6_14.

Core 2018 : A ; (Taux d'acceptation : 30,7%)

[CI16] Lili Tong, **Audrey Serna**, Sébastien George & Aurélien Tabard (2017). « Supporting Decision-making Activities in Multi-Surface Learning Environments ». Proceedings of the 9th International Conference on Computer Supported Education (CSEDU 2017), 21 avril 2017, Porto (Portugal), pp. 70-81.

ATIEF : B ; PRIX : Best Student Paper.

[CI15] Nam Tung Ly, **Audrey Serna**, Samir Aknine, Jörn Hurtienne. Towards an Integration Platform for Supporting Stakeholders in Dementia-Care Facility in Navigation. NordiCHI, 2016, goteborg, Sweden. ACM, pp.57, 2016.

(Taux d'acceptation : 28%)

[CI14] Lili Tong, **Audrey Serna**, Simon Pageaud, Sébastien George, Aurélien Tabard. It's Not How You Stand, It's How You Move: F-formations and Collaboration Dynamics in a Mobile Learning Game. In Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services (MobileHCI '16). ACM, New York, NY, USA, Sep 2016, Florence, Italy. pp.318-329,

Core 2018 : B ; (Taux d'acceptation : 24%)

[CI13] Guillaume Loup, **Audrey Serna**, Sébastien Iksal, Sébastien George. Immersion and Persistence: Improving Learners' Engagement in Authentic Learning Situations. 11th European Conference on Technology Enhanced Learning, EC-TEL 2016, Sep 2016, Lyon, France. pp.410-415, Adaptive and Adaptable Learning.

ATIEF : A ; (Taux d'acceptation : 25%)

[CI12] Eric Sanchez, Claudine Piau-Toffolon, Lahcen Oubahssi, **Audrey Serna**, Iza Marfisi-Schottman, Guillaume Loup, et al.. Toward a Play Management System for Play-Based Learning. European Conference on Technology Enhanced Learning,, Sep 2016, Lyon, France. pp.484 - 489, 2016,

ATIEF : A ; (Taux d'acceptation : 25%)

[CI11] Jean-Charles Marty, **Audrey Serna**, Thibault Carron, Philippe Pernelle, David Wayntal. Multi-device Territoriality to Support Collaborative Activities : Implementation and Findings from the E-Learning Domain. 11th European Conference on Technology Enhanced Learning, EC-TEL 2016, Sep 2016, Lyon, France. Springer International Publishing, Adaptive and Adaptable Learning - 11th European Conference on Technology Enhanced Learning, EC-TEL 2016, Lyon, France, September 13-16, 2016, Proceedings 9891, pp.152-164, 2016, Lecture Notes in Computer Science.

ATIEF : A ; (Taux d'acceptation : 25%)

[CI10] Nam Tung Ly, Jörn Hurtienne, Robert Tscharn, Samir Aknine, **Audrey Serna**. Towards Intelligent and Implicit Assistance for People with Dementia: Support for Orientation and Navigation. ACM. Interaccion, XVI International Conference on Human Computer Interaction, Sep 2015, vilanova, Spain. pp.31:1--31:4, 2015.

(Taux d'acceptation : 64%)

[CI9] Wayntal David, **Audrey Serna**, Philippe Pernelle, Jean-Charles Marty. Multi-device Territoriality to Manage Collaborative Activities in a Learning Game. 9th European Conference on Game-Based Learning (ECGBL'2015), Oct 2015, steinkjer, Norway. Proceedings of the 9th European Conference on Game-Based Learning, pp570-579, 2015.

ATIEF : B

[CI8] L.Tong, **A. Serna**, S. George, A. Tabard, G. Brochet. Interactive Surface Composition Based on Arduino in Multi-Display Environments. Dans the Ninth

ACM International Conference on Interactive Tabletops and Surfaces, Dresden. pp. 369-374. 2014.

[CI7] J. Rouillard, **A. Serna**, B. David, R. Chalon. Rapid Prototyping for Mobile Serious Games. Dans First International Conference, Learning and Collaboration Technologies 2014, Held as Part of HCI International 2014, Panayiotis Zaphiris, Andri Ioannou ed. Heraklion, Crete. pp. 194-205. Lecture Notes in Computer Science 8524. Springer . 2014.

[CI6] N. Ly Tung, **A. Serna**, S. Aknine, G. Marquardt A. Pusch. Towards an OpenStreetMap-Based Platform for Supporting Orientation and Navigation Assistance. Dans RAate 2014.

[CI5] A. Pusch, M. Brandt, **A. Serna**, S. Aknine, J. Hurtienne. How would a smart radio for people with dementia do? A case study. Dans RAate 2013, Coventry. pp. 1-2. 2013.

[CI4] M. Schubert, **A. Serna** and S. George (2012). Using Collaborative Activities on Tabletops to Enhance Learning and Knowledge Transfer. In proceedings of the XII IEEE International Conference on Advanced Learning Technologies (ICALT2012), Rome, July 4-6, 2012

[CI3] M. Schubert, Sebastien George and **A. Serna** (2012). Collaborative Learning with Tabletops: an Experimental Study. In proceedings of the 11th International Conference on Intelligent Tutoring Systems (ITS), Crete, June 14-18, 2012.

[CI2] George S., **Serna A.** (2011). Introducing mobility in serious games: enhancing situated and collaborative Learning. In Proceedings of the 14th International Conference on Human-Computer Interaction (HCII 2011), Orlando, Florida, USA – 9-14 July 2011.

[CI1] **Audrey Serna**, Gaëlle Calvary, Dominique Scapin. How Assessing Plasticity Design Choices Can Improve UI Quality: A Case Study. EICS 2010 - Proceeding of the second ACM SIGCHI Symposium on Engineering Interactive Computing Systems, Jun 2010, Berlin, Germany. pp.29-34, ⟨10.1145/1822018.1822024⟩.

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[WI6] Diana Nurbakova, Felix Bölz, Audrey Serna & Jean Brignone (2023). Towards Adaptive and Personalised Recommendation for Healthy Food Promotion. BehavRec'23, the First International Workshop on Behavior Change and Persuasive Recommender Systems. Adjunct Proceedings of the 17th ACM Conference on Recommender Systems (RecSys' 23).

[WI5] Diana Nurbakova, **Audrey Serna**, Abdelbasset Omiri & Antoine Boutet (2023). « Adaptive and Privacy-Aware Persuasive Strategies to Promote Healthy Eating Habits: Position Paper ». UMAP 2023 - 31st ACM Conference on User Modeling, Adaptation and Personalization, 29 juin 2023, Limassol (Chypre), pp. 129-131.

[WI4] Stuart Hallifax, **Audrey Serna**, Jean-Charles Marty & Elise Lavoué (2021). « Dynamic gamification adaptation framework based on engagement detection through learning analytics ». GamLA 2021 workshop.

[WI3] Hallifax Stuart, **Audrey Serna**, Jean-Charles Marty & Elise Lavoué (2018). « A Design Space For Meaningful Structural Gamification ». Late Breaking Work, CHI'18 Extended Abstracts, 21 avril 2018, Montréal (Canada), 6p.

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[WI2] Nam Tung Ly, Robert Tscharn, Jan Pressler, Stephan Huber, Samir Aknine, et al.. Smart Lighting in Dementia Care Facility. Ubicomp 2016. Workshop on Tangible Interaction with Light in the IoT, ACM, 2016, Heidelberg, Germany. pp.1636-1639.

(Conférence principale classée A dans Core 2018)*

[WI1] **Audrey Serna**, Simon Pageaud, Lili Tong, Sébastien George, Aurélien Tabard. F-formations and Collaboration Dynamics Study for Designing Mobile Collocation. 18th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct (MobileHCI 2016) , Sep 2016, Florence, Italy. Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct pp.1138-1141, 2016,

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[RN2] Élise Lavoué & **Audrey Serna** (2021). « Vers une ludification adaptative expressive des environnements numériques d'apprentissage ». STICEF (Sciences et Technologies de l'Information et de la Communication pour l'Éducation et la Formation), vol. 28, n°2, pp. 153-176.

[RN1] S. George, C. Michel, **A. Serna**, L. Bisognin. Évaluation de l'impact d'un jeu sérieux en réalité mixte. Revue STICEF 21() pp. 1-25, ISSN 1764-7223. 2014.

Articles in national peer-reviewed conferences

[CN10] Anthony Basille, Élise Lavoué & **Audrey Serna** (2023). « Présence et incarnation dans les jeux sérieux : Une revue de la littérature ». IHM '23: 34th International Francophone Conference on Human-Computer Interaction, 5 avril 2023, TROYES (France), pp. 1-12.

[CN9] Loïc Caroux, Eric Campo, Nadine Vigouroux, Eric Bourreau, Maureen Clerc, Philippe Gorce, Christian Graff, Marianne Huchard, Dan Istrate, .., **Audrey Serna** et al. (2018). « MAN : Mise en Place d'une Méthode d'Évaluation Croisée de l'Accès aux Ressources Numériques ». HANDICAP, 15 juin 2018, Paris (France), pp. 211-212.

[CN8] Guillaume Loup**, Audrey Serna** & Sébastien George (2017). « A Community-Based Development Tool for immersive interactions ». 29ème conférence francophone sur l'Interaction Homme-Machine, 1 septembre 2017, Poitiers (France), 2 p.

[CN7] Frank Sauret, Valérie Emin-Martinez, Guillaume Loup, Lahcen Oubahssi, Claudine Piau-Toffolon, Eric Sanchez et **Audrey Serna**. REARTH un exemple de Jeu Épistémique Numérique De la conception à l'expérimentation. Colloque Enseignement des Technologies et des Sciences de l'Information et des Systèmes (CETSIS), May 2017, Le Mans, France. 2017.

[CN6] Valentin Lachand, **Audrey Serna**, Aurélien Tabard, Jean-Charles Marty. De l'efficacité de visualisations indicielles ou symboliques pour la régulation d'activités collaboratives. Actes de la 28ième conférence francophone sur l'Interaction Homme-Machine, Oct 2016, Fribourg, Suisse. pp.144-154, 2016, Actes de la 28ième conférence francophone sur l'Interaction Homme-Machine.

(Taux d'acceptation : 64%)

[CN5] Guillaume Loup, Sébastien George, **Audrey Serna**. Fondements et caractérisation des jeux épistémiques numériques pervasifs. Sébastien George, Gaëlle Molinari, Chihab Cherkaoui, Driss Mammas et Lahcen Oubahssi. 7ème Conférence sur les Environnements Informatiques pour l'Apprentissage Humain (EIAH 2015), Jun 2015, Agadir, Maroc. pp.41-52, 2015.
(Taux d'acceptation : 40%)

[CN4] K. Sehaba, **A. Serna**. Serious game pour le décodage des situations sociales chez les adolescents Asperger. Dans Handicap 2014, 8ème congrès sur les aides techniques pour les personnes en situation de handicap, les technologies d'assistance : de la compensation à l'autonomie. Paris. pp. 132-137. ISBN 978-2-9536899-4-5. 2014.

[CN3] **Audrey Serna**, Gaëlle Calvary, Dominique Scapin. Penser "Plasticité" peut améliorer la Qualité des Interfaces Homme-Machine : une étude de cas. Ergo'IA '10 Proceedings of the Ergonomie et Informatique Avancee Conference, Oct 2010, Biarritz, France. pp.77-84, ⟨10.1145/1868650.1868663⟩. ⟨hal-00953324⟩

[CN2] **Audrey Serna**, Helene Pigot, Jérémy Bauchet, Sylvain Giroux, Vincent Rialle, et al.. Recommandations ergonomiques pour la conception de systèmes d'assistance cognitive dans les habitats intelligents. ERGO'IA 2010 : 12ème Conférence Internationale Ergonomie et Informatique Avancée : Innovation, Interactions, Qualité de vie, Oct 2010, Biarritz, France. pp.3 - 10, ⟨10.1145/1868650.1868652⟩. ⟨hal-01309287⟩

[CN1] **Audrey Serna**, Sébastien Pinel, Gaëlle Calvary. La plasticité des IHM en action : un exemple de téléprocédure plastique. proc. IHM'09, 21ème Conférence Francophone sur l'Interaction Homme-Machine, 2009, Grenoble, France. pp.359-362.

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[WN4] Marceau Nahon, Aurélien Tabard & **Audrey Serna** (2024). « Capturing stakeholders values and preferences regarding algorithmic systems ». IHM'24 - 35e Conférence Internationale Francophone sur l'Interaction Humain-Machine, 29 mars 2024, Paris (France).

[WN3] Elise Lavoué, Emma Guttierrez & **Audrey Serna** (2021). « Exploring the physicalization of motivational data in the acquisition of good sleep behaviors for adolescents ». 32ème conférence internationale francophone sur l'interaction homme-machine, 13 avril 2021, Metz (France).

[WN2] **Audrey Serna**, Anagael Pereira & Elise Lavoué (2021). « A design space for the exploration of motivational affordances continuity in hybrid learning environments ». 32ème conférence internationale francophone sur l'interaction homme-machine, 13 avril 2021, Metz (France).

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[ESO1] **A. Serna**, S. George. IHM avancées pour l'apprentissage. Workshop in conjonction with EIAH 2011, Mons, Belgique. pp. 61. 2011.

Book chapters

[CO5] Michel C., **Serna A.**, Chalon R. Chapitre 6 : Le grand Lego des données et des services. Architecture de l'information : Méthodes, Outils et Enjeux, sous la direction de B. Habert et JM. Salaün, pp.119-138, 2015.

[CO4] Calvary G., Dupuy-Chessa S., **Serna A.** (2012). Adaptation des IHM. Chapitre dans « L'adaptation dans tous ses états », coordinateurs de l'ouvrage : Philippe Lopistéguy, Philippe Roose et Dominique Rieu. Editions Cépadues.

[CO3] Calvary G., **Serna A**., Coutaz J., Scapin D., Pontico F., Winckler M. (2011). Envisioning Advanced User Interfaces for e-Government Applications: a Case Study. In Practical Studies in E-Government. Best Practices from Around the World, pages 205-228, Assar, S.; Boughzala, I.; Boydens, I. (Eds.).

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[CO1] Gaëlle Calvary, **Audrey Serna**, Christophe Kolski, Joëlle Coutaz. Les transports : un terrain fertile pour la plasticité des Interfaces Homme-Machine. C. Kolski. Interaction homme-machine dans les transports - information voyageur, personnalisation et assistance, Hermes Lavoisier Publications, Paris, pp.287-312, 2010.

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