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Abstract

Illicit drug use among higher education populations is a recognized public health issue. Existing interventions only partially manage to reduce the harm drugs can cause in this population. Reasons for this include the absence of personalized behavior change components focusing on students' needs for harm-reduction practices. To address this issue, we built a clinical algorithm that rapidly assesses the needs of students and offers them immediate support through the provision of tailored harm reduction practices. This algorithm was informed by relevant behavior change theories and outputs from Information System (IS) research. In this paper, firstly, we discuss how we developed the clinical algorithm, leveraging personalized data analytics which are used in a decision rule manner. Secondly, we demonstrate how the algorithm is implemented within the intervention, namely MyUSE, through the use of examples. The artifact is currently in its final development phase and evaluation of its usability, feasibility, and effectiveness will follow.

Keywords

Clinical algorithm, behavioral change techniques, modularized intervention, harm reduction, higher education students

Introduction

The increased number of students in higher education who use illicit drugs and the possible adverse consequences of this use (e.g., lower grade point averages, poor class attendance, heavy drinking, etc; Arria et al. 2015; O'Grady et al. 2008; Pedrelli et al. 2015) prioritize actions towards effective harm reduction practices. Digital behavior change interventions, delivered through the use of mobile apps and online platforms, are highly acceptable to student populations as a means of harm reduction in higher education institutions (Organ et al. 2018). Despite their popularity, these interventions produce only modest success in reducing use and subsequent harm from drugs (Dick et al. 2019). One of the reasons for this is the absence of personalized behavior change components which address students' needs for harm-reduction practices in their context of use (Vasiliou et al. 2020).

Contemporary behavioral science can now supply IS with the appropriate knowledge with regards to which behavior change techniques- the active ingredients of an artifact – can be used to support behavior changes (Connell Bohlen et al. 2019; Michie et al. 2013). However, so far IS researchers have rarely applied this knowledge in the context of student drug use to develop more clinically useful artifacts (Organ et al. 2018). IS researchers can now systematically look at how they can use the outputs from design science research (DSR; Peffers et al. 2007) and information technology (IT), such as personalization algorithms, to develop agile, personalized, and modularized artifacts. In turn, the appropriate use of these outputs can create artifacts which can accelerate an intervention adaption (Hekler et al. 2016) and address, successfully, the need for more personalized harm-reduction interventions (Organ et al. 2018). Personalized data analytics can be used in a decision rule manner where users will receive only the components they need from the digital behavior change intervention (Bates et al. 2014). This paper presents MyUSE "My Understanding of Substance-use Experiences" and demonstrates how an algorithm is used within a digitally delivered artifact (Dick et al. 2020). Through a series of mock-ups, we illustrate the function of the algorithm, and how it provides personalized behavior change techniques to higher education students who use illicit drugs.

MyUSE

MyUSE aims to reduce the harms from drug-use among higher education students (Dick et al. 2020). It employs a combination of 29 behavior change techniques (BCTs) that were identified in a large mapping exercise (Vasiliou et al. 2020) using the Behavioral Change Wheel Framework (Michie et al. 2013) and the Behavior Change Technique Taxonomy v1 (BCTTv1) (Michie et al. 2013). The 29 BCTs are distributed across eight identified clusters of behaviours, MyUSE attempts to change which all focus on three goals: (a) to increase mindful decision-making with respect to drug-use, (b) promote alternatives to drug-use activities, and (c) cultivate context-specific harm-reduction practices in higher education (Vasiliou et al. 2020).

We developed a new clinical algorithm that was designed to provide a personalized, multicomponent intervention. Users of the artifact get only the components needed, based on their personal drug use history and drug type assessment. The algorithm is used from the assessment baseline data (users' inputs) to generate personalized feedback messages and provide users with knowledge that can help them increase their awareness of the impact of drug use in their college life. Then, as part of the users' journey, a series of harm-reduction practices and contextual behavior change skills are provided. The MyUSE digital intervention utilizes a careful delineation of users' inputs and outputs to provide personalized feedback and skill-based activities and predict specific short-term outcomes per module (e.g., increased knowledge about the harms per drug type and frequency) and distal outcomes across modules (e.g., increase mindful behavioral awareness in relation to drug use decision making).

The usefulness of the Clinical Algorithm in users' two-phase journey

The MyUSE prototype consists of 11 modules which function in two phases: the profile building phase (module 1 to 4) and the skill-building phase (modules 5 to 11). As figure 1 illustrates, we use the MyUSE clinical algorithm on the profile phase (beginning from module 1), to help users build their profile with the risk of harms from drug use (none, low/moderate, or substantial/severe) and identify areas where they may lack skills in relation to harm-reduction practices (modules 2 to 4; e.g., lack of knowledge, poor awareness of decision making, lack of alternatives, etc. for a full explanation see Vasiliou et al. 2020).

Next, based on their data inputs, users are assigned to a personalized skill-building journey (Phase II). In this phase, users get modularized contextual-behavior change skills relevant to harm reduction at student population level, such as how they can be more mindful in their decision to take drugs, understand their triggers, behaviours, and consequences of their drug use, and identify value-based alternatives to drug use activities.

Programmatic planning of user's inputs (e.g., responses to questionnaires), originating from the profile building journey (phase I) are algorithmically paired with user's specific outputs at the personalized skill-building journey (phase II). Each pair of input and output data is structured in a carefully developed way so that they reflect the objectives of one of the eight clusters of drug use behaviours that were identified in our previous mapping work (Vasiliou et al. 2020). For example, as figure 1 shows, if users score below the mean in questionnaires assessing behavioral awareness (module 2a), they are algorithmically allocated to get a corresponding skill-based module in phase II (e.g., module 3) which targets increasing users' mindful awareness in relation to their drug use. This is the case for other key modules within MyUSE.

The delivery of the MyUSE activities is administered programmatically from the Content Management System (CMS), Decision Tree Rules Engine, and Feedback Generator. Together, these interface systems function the MyUSE Clinical Algorithm. The layout and content of each page are entirely configurable by people with basic technical skills within the CMS which increase the team's direct contribution to the CMS. Figure 2 illustrates a typical page outline within the CMS utilizing the Multiple-Choice custom component. As shown, the identifiers and configurable options, assigned to the component, become functional on render of the page.

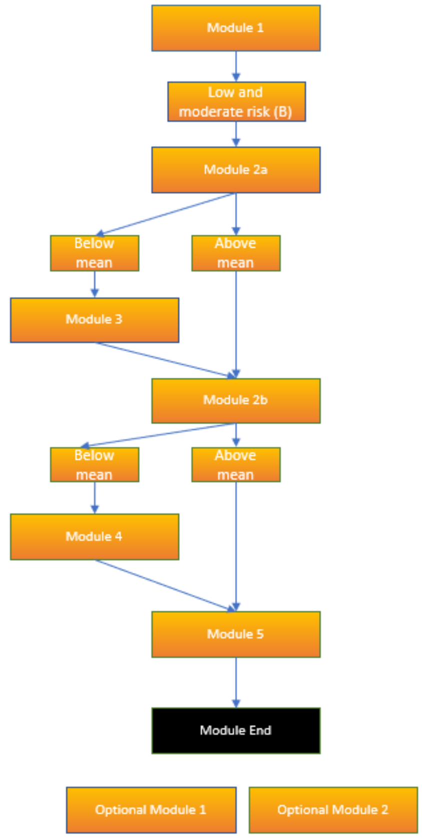
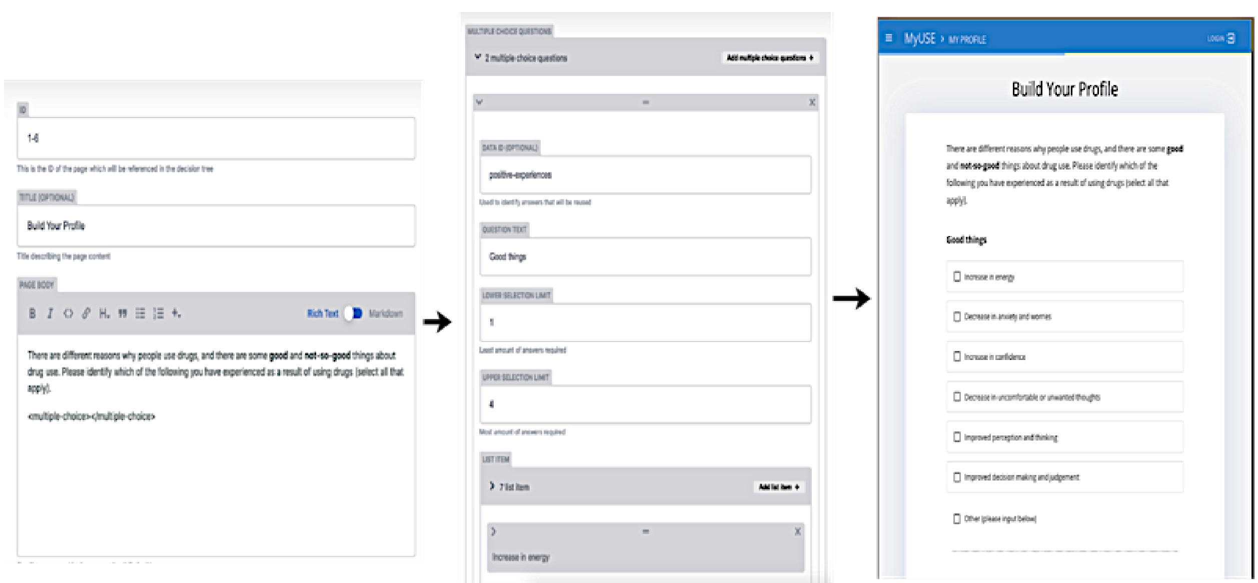


Figure 1. MyUSE Module Mapping stratification



Typical page content within the CMS, placing textual content and custom components on page through markdown

Configure and assign identifier to each item within the multiple choice component

Final component rendered to browser window

Figure 2. Typical page outline within the CMS

As users progress through the intervention, they are asked for inputs in different interactive components (e.g., define and record three value-based goals while in college). These inputs are stored using unique identifiers, which are used to recall the appropriate feedback content matching this identifier.

In addition, each item of feedback is also assigned an identifier which, when published, is stored as YAML front matter within markdown files. Once a user completes a page, any relevant recorded inputs are processed to determine the next page identifier, using the Decision Tree Rules Engine. This identifier is used to retrieve the appropriate markdown file. The second stage of this process organizes the appropriate feedback to display on this page before render. Figure 3 shows the typical page structure recalling user answers and placing dynamic feedback at the bottom of the page. The feedback generator chooses pre-defined content, based on users' prior answers (inputs).

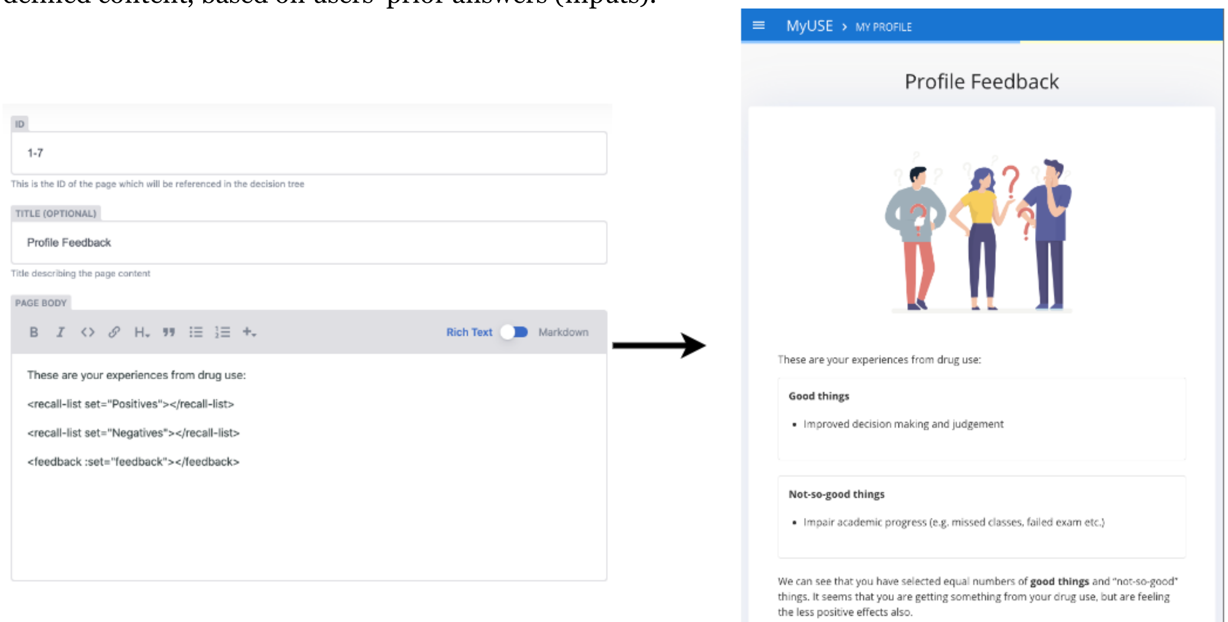


Figure 3. Typical page structure with input from users' responses showed at later phase

Each page within the MyUSE application has an associated set of 'rules' (within the Decision Tree Rules Engine) and content (within the CMS). These rules dictate the conditions required to move to the next page, as well as any number of conditions to determine what the next page should be. Figure 4 illustrates the typical processes invoked on navigation between pages. This process can occur either on page load or on interaction with on-screen components.

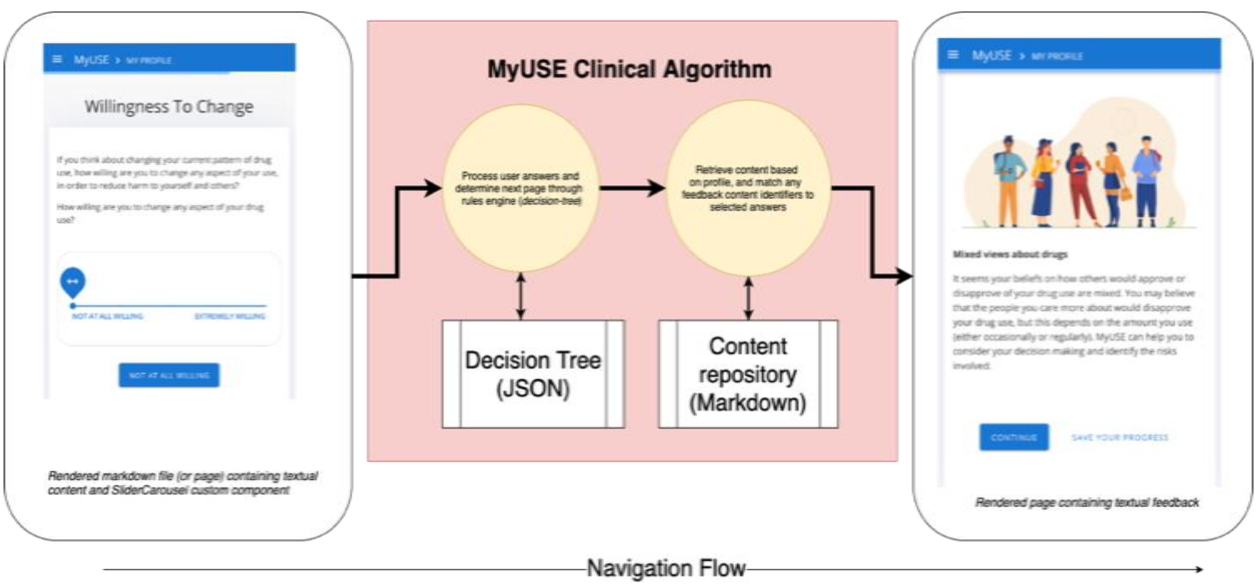


Figure 4: Example of dynamic feedback generation process

On page completion, the Feedback Generator adjusts the content to be displayed within the next page, based on a variety of conditions that include prior user answers and profile attributes. Available feedback for each page is created within the CMS, assigned a data identifier, and rendered locally within the content repository as part of the page YAML front matter markdown.

An example of how the MyUSE clinical Algorithm is used

Within the MyUSE platform, the direct inputs enter the system to support the algorithm deployment across different modules and within the two-phase user journey. Figure 5 illustrates how the algorithm orders are implemented in one of the modules (Module 1) supported by the CMS, the Decision Tree Rules Engine, and the Feedback Generator infrastructures.

Firstly, all users, regardless of the type and level of use, enter the platform and begin their journey by responding to the drug use screener question (see blue box with number 1. Drug use screener, on figure 5; e.g. *in the past 12 months, have you used drugs other than those required for medical reasons?*). Depending on the user's response, the clinical algorithm allocates individuals into "no" or "yes" pathways which enact the user's journey within MyUSE. Students reporting no drug use start their journeys from the green box with number 3A Quiz (see fig. 5). Students who report drug use start their journey from the blue box with the number 2. Primary Drug (see fig. 5).

A student (i.e user of the artifact) who reports no drug use begins their journey with a quiz test about their drug-related knowledge (#3A; e.g., a binary response in a quiz question, such as "*it's illegal to have drugs in your system*). Depending on the user's answer, direct personalized feedback is provided (e.g., *It's not against the Irish law to have drugs in your system. If you need medical assistance after taking drugs, please call an ambulance. You will not get in trouble. However, sale and possession of drug use in Ireland is illegal and carries penalties*). An overall score of the knowledge about drug use is provided (#4A), along with prompts for the users to continue with further activities (#11). MyUSE activities for students who do not use, aim to increase awareness of the potential effects of drugs in students' college life. Others attempt to help students strengthen value-based activities and behavioural awareness of the potential influences of their behaviours.

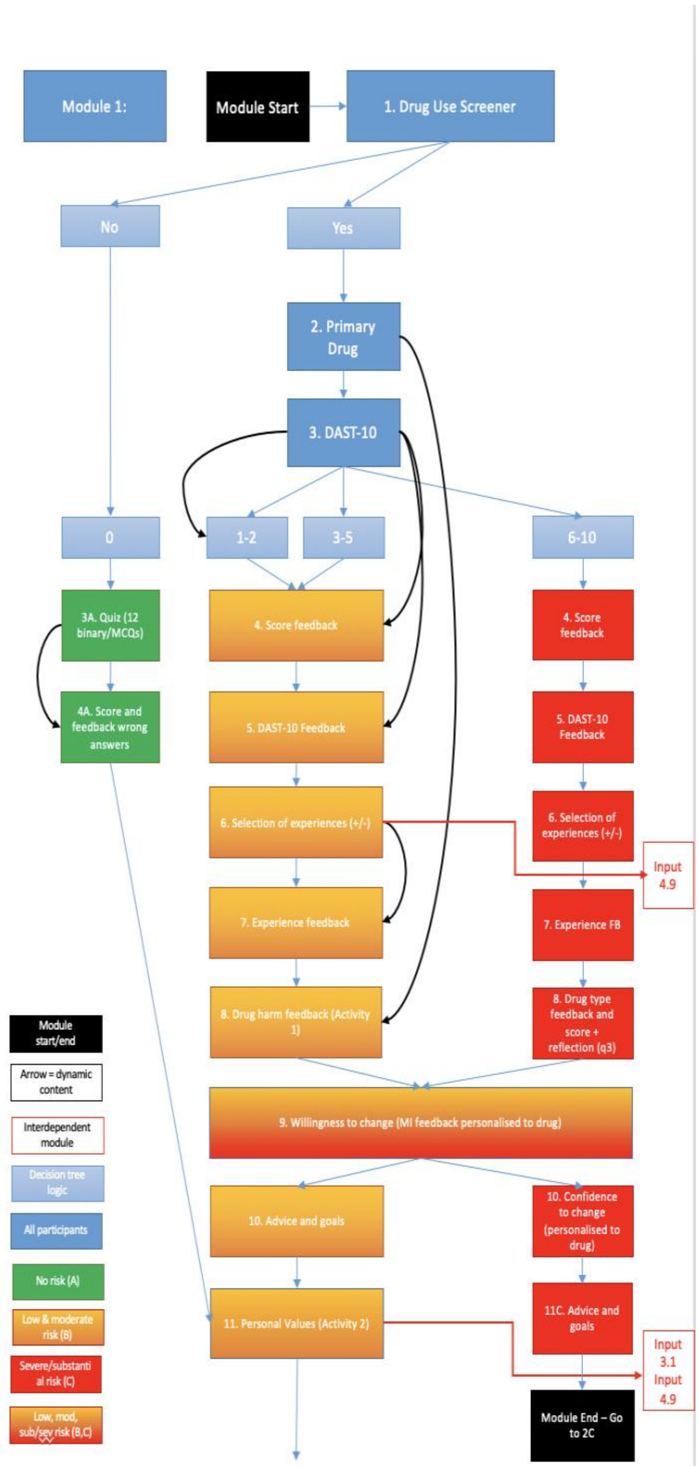


Figure 5. Module 1 Clinical Algorithm mapping

Students reporting drug use begin their MyUSE journeys with an assessment of the risks and harms from their primary drug use (see fig. 5; #3; DAST-10; McCabe and Cranford 2006). Based on their scores, they are algorithmically allocated to either low/moderate or substantial/severe risky user's pathways (see fig. 5; #4), as calculated by the Drug Abuse Screening Test (McCabe and Cranford 2006). Then, several consecutive activities attempt to increase awareness of the consequences of students' use in their college's lives. Here, students' inputs are used by the algorithm to deliver personalized information. Depending on the score students' get in a series of questionnaires, assessing the impact of drug use in their lives, different feedback is provided. Activities include norm correction (e.g., perceived % of the students using drugs in their college vs. actual %), gamified provision of accurate information about the harms, risks, consequences of drugs in college life, and activities focusing at eliciting and exploring the students' reasons for use and/or their levels of change through a motivational interviewing-style and a tone of acceptance and compassion (Vader et al. 2010). Following this, students are further algorithmically allocated to receive personalized, modularized harm-reduction practices and skills (personalized skill-building journey; phase II) which are relevant to their own needs (based on their assessment in the profile-building journey; phase I).

All activities for both using and non-using students are informed by modern behavior change frameworks, such as the Psychological Flexibility (Ciarrochi et al. 2016) which promotes responding to drug use with an awareness of the potential influences of behaviours and recognition of the potential consequences of this responding, based on what is important for the students' future goals.

Conclusion

MyUSE is a new clinical algorithm that harnesses cutting-edge DSR and behavioral science to develop an innovative personalized, modularized, contextual behavior change digital artifact for higher education students' drug use. The demonstration of how the design science outputs were used in an IS framework for the development of the algorithm was found to be a complex process. Two of the main issues relevant to the MyUSE clinical algorithm considered include: 1. how the research team defined the criteria for the evaluation of the MyUSE and 2. how it leveraged IS to support ongoing design and development changes to the artifact.

To begin with, the research team decided to employ the Design Science Research Methodology (DSRM; Peffers et al. 2007) to map the success criteria for the evaluation of the artifact. Towards this aim, we decided that the evaluation should be on-going and occur in different phases of the artifact and algorithm development. In the early phase of the artifact's development, the research team proceeded to a formative evaluation of the first low fidelity mock-ups (e.g., using cognitive walkthrough and iterative usability testing methods) to identify any technical problems and define points of improvements. The early usability testing of the low fidelity mock-ups with students enabled understanding of the design requirements needed for the algorithm and the artifact. It also provided valuable knowledge for improving the clinical sensitivity of the algorithm's functioning (e.g., in which modules algorithms should be prioritized) within the artifact. All these occurred before developing the proof-of-concept-level prototypes, allowing the team to make changes as the project unfolded and without consuming unnecessary time or effort in tasks that needed modifications. Currently, the research team is planning to evaluate the performance of the MyUSE clinical algorithm and artifact, assessing their efficiency in targeted clinical outcomes, including changes occurring in students' drug use behaviors, and reductions of the negative consequences of drug use at students' lives. For this evaluation phase, the team will employ a mixed-method design approach (e.g., a fractional factorial randomized controlled trial and pilot testing) where both the sociotechnical and clinical perspectives of the artifact will be assessed. By combining the methods, we will be able to understand how the original design requirements are satisfied, what is the usefulness of the clinical algorithm, and what should change before a further evaluation and generalization of the artifact are implemented in non-experimental, educational settings.

Another complex issue worth mentioning is the foundation of a common language for the development of the artifact that was adopted across the different disciplines. This was achieved during the early phase and through an a priori establishment of the IS and IT requirements needed for the development of the algorithm. A common language translating IS terminology in a way that it could be understandable for non-IS members of the team (e.g., behavioral and implementation scientists) provided a hub for parallel work task management and a channel for continuous communication without disruptions. For example, the configurability of the layout and content of each page allowed non- IS team members' to directly contribute to the CMS building platform, saving time for other important working tasks (Dillon et al. 2020). Leveraging smart systems that can be agile and flexible to incorporate on-going changes during the whole cycle of new algorithms were key activities that bridged the pragmatic gap between technology, contextual behavior science, and implementation.

Overall, the use of the DSRM phased methodology in this study helped in further spring-boarding the synergy of IS and contextual behavior science in a joined effort to leverage carefully created algorithms and artifacts. In this paper, we emphasize the use of specific outcomes originating from IT, DSR, and contextual behavior science that contributed to different layers of the artifact's development. The "lesson learnt" from this work is that the complexity of drug use behaviours and how these can be addressed, clinically, technically, and digitally require intensifying the symbiosis of multidisciplinary teams that make use of behavioral science, personalized applications, and sensitive clinical algorithms to effectively address emerging societal pandemics, such as the increased drug use among higher education populations. It was through this framework that the MyUSE was built. Future work includes a full clinical, technical, and economic evaluation of the MyUSE and implementation of the platform to different educational settings. Additionally, the security of the long-term effectiveness of MyUSE through longitudinal data gathering and analyses will highlight further points of refinements of the digital platform that will go along with the ongoing changes in the technology, the society, and the developmental trajectories young adults face.

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