Modelling user reactions expressed through graphical widgets in intelligent interactive systems

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Modeling user reactions expressed through graphical widgets in intelligent interactive systems

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Abstract
Nowadays, most interactive social systems allow users to react to their contents, and exploit user reactions to provide intelligent behaviours, such as adaptation or recommendation. Therefore, carefully understanding and designing the user/system dialogue that revolves around reaction provisioning is a crucial aspect.
In this paper, we introduce the UpRISE model with the aim of formally describing the user/system interaction while providing and using reactions. Then, we show how this model can be used to formally represent and describe interactive social systems that collect user reactions, as well as to compare them. In addition, we exemplify how the UpRISE model can provide a sort of checklist that stimulates system designers to approach design/redesign tasks involving user reactions in a thorough and well-structured manner, suggesting all the possibly relevant points with respect to different usability and performance-related goals. This approach can be seen as the first step towards more transparency in the design of intelligent interactive systems.

KEYWORDS
interaction design; user interface; reactions model; intelligent interactive systems

1. Introduction

Following the advent of Web 2.0, users are acquiring a more and more crucial role, given their increasing possibility to interact with web systems and applications. Users are not merely passive consumers of system-provided contents: conversely, they can directly communicate with the system to express appreciations, criticisms, opinions, interests or emotions with respect to the contents they are provided with. To do so, they can use different graphical interface controls (i.e., widgets) to express ratings, add emoticons, or write textual comments. Almost all websites (from media providers like Netflix[1] to social networking sites like Facebook[2], from social media sites like YouTube[3] to commercial platforms like Amazon[4]) are currently allowing users to *react* to their contents. Here, we define a reaction as *an explicit action taken by the user via a widget in order to manifest either a real or expected interest, an evaluation or an emotion towards an object of the system.* thus, we focus on reactions provided through graphic interface widgets, i.e. elements of a graphical user interface which provide a specific way for a user to interact with an application, such as rating scales, emoticons, likes, etc. In this sense, we likewise consider textareas as graphical interface widgets, which are used to convey reactions through text.

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[1]https://www.netflix.com/

[2]http://facebook.com/

[3]https://www.youtube.com

[4]https://www.amazon.com/

User reactions are very important: they are a valuable means to better know users, and can be used to provide intelligent behaviour. The intelligent interactive systems that allow to express reactions are different in terms of aims (e.g. providing media content, favouring relationships, etc.), and data usage, i.e., how they exploit data to deliver an intelligent behaviour (e.g. to predict user interests and generate recommendations (Ricci, Rokach, Shapira, & Kantor, 2010), to personalize the system interface, etc.). For these reasons, it is crucial to carefully design the modalities for enabling user reactions, from the specific interface widgets that can be used to convey reactions to system responses, and it is therefore fundamental to provide designers with some methodological tool able to help them in the design process.

Currently, in the Human-Computer Interaction state of the art, it is possible to find formal models regarding either global aspects of human interaction with any system, such as tasks and goals (see e.g., GOMS (Card, Moran, & Newell, 1983)), or vocabularies and metaphors that allow to characterize the interaction with specific devices (see e.g., KAM (MacKenzie, 2003)). In contrast, to the best of the authors' knowledge, according to the ACM Digital library and Google Scholar, no previous work is devoted to the formal modeling of user reactions and of the dialogue that occurs between users and systems when such reactions are exchanged. Similarly, in the literature, interactive systems are studied from different perspectives, from performance and usability evaluation (for example (Norman, 2002; Paramythis, Weibelzahl, & Masthoff, 2010; Rastogi & Singh, 2016)) to decision making (for example(Cheung & Lee, 2010; Jameson et al., 2014)) and interaction modalities (Ishanka & Marasinghe, 2015), but no work specifically examines user reactions. Focusing on a particular type of reaction, i.e., the ratings given by means of rating scales, Cena et al. (2017) studied how the scales themselves impact on user ratings. Also in this case, however, a general formal model that describes the rating process is missing. Differently from (Cena et al., 2017), we aim at considering other types of user reactions beside ratings, such as emotions, engagement, etc.

The goal of this paper is to fill this gap by proposing the UpRISE (**U**ser **P**rovided **R**eactions in **I**nteractive intelligent **S**yst**E**ms) model, which aims at formally describing all the components of systems which allow users to provide a reaction and then exploit it to provide intelligent behaviour. Besides representing an analytic tool, this model could stimulate system designers to ask themselves the right questions and take into account all relevant aspects of the system at hand. We envisage that UpRISE could also provide the basis for a predictive model, for instance once stable correlations among system performances and their reaction-related features are learned.

It is important to note that our model does not aim at representing the specific meaning expressed through user reactions (which would require specific techniques for both textual and non-textual content). Instead, it is rather focused on the formalization of the dialogue that is developed between the system and its users.

The main contribution of our work is providing a formal model that can be used in the following ways:

- as a descriptive tool, to describe interactive systems that make use of reactions in a formal way;
- as a comparative tool, to analytically compare interactive systems that exploit user's reactions;
- as a reference design model, to design the user-system dialogue in reaction-based interactive intelligent systems.

In order to develop the UpRISE model, we adopted a "top-down" approach. We started from a previous model by Cena and Vernero (2015) which describes rating scales. Then, in order to include other widgets, we examined relevant literature to identify already-existing works modeling user reactions (see section 2). Afterwards, we defined the UpRISE model based on our knowledge of interactive intelligent systems. Finally, we validated the model using it to describe real life systems.

The paper is structured as follows. Sections 2 and 3 provide background information: in particular, Section 2 discusses state of the art work on reactions, while Section 3 compares UpRISE with related existing HCI models, highlighting their limits with regards to our goals. Section 4 describes our formal model in detail. Sections 5 and 6 validate UpRISE as a tool to -respectively- describe and compare real life systems. Section 7 shows how UpRISE can be used to help designers to identify and explore novel areas of the design space, by providing a ready-to-use checklist for the design of interactive systems which allow reactions. Finally, Section 8 concludes the paper with a discussion of limitations and future work.

2. Related work

In the literature, user reactions have been studied from different perspectives, for example, investigating how they can be exploited by intelligent systems like recommenders (Adomavicius & Tuzhilin, 2005; Ricci et al., 2010), or studying the best widget to use to gather user reactions (Gutwin, Roseman, & Greenberg, 1996; Nielsen, 1993), but not from the point of view of a user-system dialogue, as we propose in this paper.

2.1. Reactions in recommender systems

Recommender systems provide recommendations of items of interest for the user, inferring such interest from user reactions usually given in the form of ratings (Adomavicius & Tuzhilin, 2005; Ricci et al., 2010). Thus, the topic of gathering valuable ratings from users is particularly relevant, since the recommendation performance depends on ratings themselves. However, few works focus on rating scales, highlighting the influence of scales on user ratings, such as (Cena et al., 2017), who found that rating scales features impact the rating, Vaz, Ribeiro, and De Matos (2013), who compared the performance of a collaborative filtering algorithm using ratings expressed on two scales with different granularity, and Cosley, Lam, Albert, Konstan, and Riedl (2003), who studied the effect of different scales on user ratings also in relation to MAE. Kluver, Nguyen, Ekstrand, Sen, and Riedl (2012) studied the problem of noise in user ratings, which may affect the accuracy of recommender systems. To address this problem, they developed the preference bits framework to help designers measure, understand, and reduce noise, by means of a set of metrics to assess the amount of information users give and and how much information they receive.

Most of the studies in this area focused on other aspects, such as the design of rating scales and the effects of user's personality on rating behavior. Referring to the design of rating scales, Swearingen and Sinha (2002) suggested to adopt a mix of different types of questions; Herlocker, Konstan, Terveen, and Riedl (2004) pointed out that an appropriate rating scale should allow users to distinguish among exactly as many levels of liking as it makes sense to them. Van Barneveld and Van Setten (2004) found that most users prefer to have predictions presented by means of 5-star interfaces, while they are less in agreement regarding interfaces to provide input to the system, consistently with the findings of Cena, Vernero, and Gena (2010). Usman, Alghamdi, Tariq, and Puri (2010) proposed a Relative Ranking, where a benchmark item is used to compare other items. Sparling and Sen (2011) investigated the mental effort and time associated to rating scales with different granularities, finding that users' average rating time increases with the granularity of rating scales, while there are no significant differences as far as cognitive load is concerned.

2.2. Studies about interface widgets

Reactions are usually studied from the point of view of the graphical cues used to convey user reactions, i.e. the interface widgets. The most studied widgets are the rating scales and emoticons. Few studies have been devoted to the investigation of the use of other interface widgets, such as buttons, check-boxes, sliders and so on, but especially from a usability point of view (Gutwin et al., 1996; Han & Park, 2009; Nielsen, 1993).

Rating scales widget Due to the importance of user reactions in form of ratings for recommender systems seen above, a specific attention has been devoted to the rating scale widget. Relevant works generally focused on the study of how specific features, such as granularity, neutral point or labeling, can affect the final rating. For example, regarding the optimal *granularity* in the rating scales, Lim (2008) found that higher granularity causes higher ratings; Preston and Colman (2000) and Weng (2004) found that granularity can impact the response reliability, concluding that high granularity is more reliable and preferred by users. Shaftel, Nash, and Gillmor (2012) demonstrate that the best granularity depends on the item content and purpose, and thus the decision is domain-dependent. Regarding the *impact of the neutral point on ratings*, Garland (1991) found that the mid-point can be chosen in order to provide a less negative answer, because of a social desirability bias. Weijters and Schillewaert (2010) found that it causes a higher net acquiescence response style, i.e., the tendency to show more agreement than disagreement, a lower extreme response style and a lower level of misresponse to reversed items. About the *labelling*, Weijters and Schillewaert (2010) found that the format of a rating scale can bias the mean, variance and internal consistency of the collected data. Friedman and Pollack (1993) studied the effect of the polarity of the labels, providing evidence of a bias towards the left side of a scale, possibly due to factors such as reading habits or a primacy effect. Weijters and Schillewaert (2001) show that the negative evaluation side of a scale is perceived as more negative when it is labelled with negative rather than positive numbers.

Emoticon widget Emoticons are small images or conjunctions of diacritical symbols, which represent moods, facial expressions and activities which can be considered non- verbal substitutes for communicating emotions and feelings in a text-based environment Rezabek and Cochenour (1998). Emoticons representing an abstract depiction of a human face are perceived in the same manner as the corresponding facial expression. Since they are very versatile and can convey different types of information (emotion, mood, activies, objects..), emoticons have been mainly studied in order to verify what they can convey, especially in relation to emotions and mood. Yuasa et al. Yuasa, Saito, and Mukawa (2006) showed that a smiling emoticon activates the same brain areas as the image of a person smiling and can therefore be considered as a representation of that emotion. Other studies focused on other emoticons (Ruan, 2011) such as the ones representing actions (dancing, jumping, singing) or objects (sun, heart, rain), or a specific mood not associated with a particular facial expression (tired, bored, creative). Most of the studies focused on the interpretation of the emotions conveyed by the emoticons, exploiting sentiment analysis techniques. We can cite Rojas et al. Rojas, Kirschenmann, and Wolpers (2012) which performed a sentiment analysis on text-based chat-logs on Skype, disregarding all verbal information and using only emoticons to detect positive sentiments, demonstrating that emoticons do indeed represent a strong indicator for detecting positivity within chat communication. Another example is Hogenboom et al.

Hogenboom et al. (2013), which exploited an emoticon sentiment lexicon in order to improve a state-of-the-art lexicon-based sentiment classification method, demonstrating that using emoticons significantly improves sentiment classification accuracy. This indicates that whenever emoticons are used, their associated sentiment dominates the sentiment conveyed by textual cues and forms a good proxy for the intended sentiment.

3. Background: interaction and formal models in HCI

Models and formal methods have long been used in HCI (Carroll, 2003). Models are simplified representations of reality (MacKenzie, 2003) or of some aspect of HCI (Rogers, 2012), whose goal is to help understand the functioning of complex artifacts or phenomena, and eventually support their design and evaluation. As already introduce above, models have been generally categorized as *descriptive*, *predictive*, *generative* (Carroll, 2003), and sometimes *comparative* (Beaudouin-Lafon, 2000). In this perspective UpRISE, as also demonstrated in Sections 5, 6 and 7, can be considered descriptive, comparative and prescriptive. One of its limits is not being predictive, limit that we will try to overcome in the future, as will be described in Section 8.

Descriptive models such as the *key-action model* (KAM) (MacKenzie, 2003) and Buxton's *3-state model* (Buxton, 1990) can be considered similar to UpRISE in that they provide analysts and designers with a pre-defined set of terms or features that are domain-dependent, however, they both focus on different domains: keyboard keys and the operation of a mouse in terms of state transitions, respectively. UAN (User Action Notation) (Hartson, Siochi, & Hix, 1990) provides a formal notation for the representation of interface designs, allowing to describe the association between user actions and system feedback and state, similarly to operations in UpRISE. Differently from UpRISE, however, UAN narrowly focuses on the interface level, disregarding the meaning of user actions in the context of an intelligent system. Finally, the Instrumental Interaction model by Beaudouin-Lafon (2000) describes interfaces as collections of elements (e.g., menus or scrollbars) that act as mediators (*interaction instruments*) which allow to manipulate objects of interest in the physical world (*domain objects*), similarly to widgets in UpRISE. Furthermore, both the Instrumental Interaction model and UpRISE link user actions on domain objects to the corresponding system-provided feedback (see the "system provides response" operation in UpRISE). Also in this case, however, there is a focus on the interface, while feedback which is decoupled from the interaction instrument is not represented, and the meaning of user actions is out of the scope of this model.

Among predictive models, GOMS (Goals, Operators, Methods, Selection rules) is a family of models (Card et al., 1983) which focus on the procedural knowledge users need to carry out tasks (Kieras, 1994), can be used to improve interaction efficiency and are domain-independent. However, similarly to UpRISE, KLM (Keystroke-Level Model, (Card, Moran, & Newell, 1980)) and TLM (Touch-Level Model), two specific techniques that instantiate the GOMS on keyboard and touchscreen interaction, restrict the set of operations that analysts can take into account to a specific domain. Differently from UpRISE, GOMS models aim at predicting how expert users carry out their tasks, producing quantitative predictions and allowing for the comparison of alternative methods.

Finally, it should be noted that the scope of HCI models dealing with human behaviour only partially overlaps with the scope of UpRISE. In fact, they usually concentrate on the users' point of view, see e.g. Norman's well-known Seven Stages of Action Theory (Norman, 1988), disregarding the fact that the system can also play an active role and use the interface as a means to communicate. Even in Abowd and Beale's Interaction Framework (Abowd & Beale, 1991), which also considers the role of the system, interaction cycles are always initiated by users.

For the UpRISE model we adopt a formal notation which can be used not only to formally describe systems, but also to automatically create some visualisation such as the one in Section 6 for comparing systems. An alternative way to look at formal methods applied to interactive systems is provided by Dix (2003). According to Dix, formalisms can allow to simulate behavior with no need for a running system. Formal methods may provide analysts with ad-hoc mathematical calculations (as in the aforementioned GOMS-based models or Fitts' law), dialogue simulations (i.e. state transition networks), executable system models (see model-based user interfaces below). According to Dix, a successful formal method should be: useful, appropriate, communicative, complementary, fast pay back, responsive, reliable, of quality, maintainable. Among all these qualities we believe that UpRISE could be defined complementary, since it offers some paradigm that differs from implementation, allows one to *see the system from a different perspective*, in this case one more suitable for producing and assessing the interface design. In our case we found useful to make use of a formal description, since the complex interactions between simple elements may be hard to make sense of and can lead to emergent effects that do not show up during normal testing.

Model-based user interfaces (Meixner, Paternò, & Vanderdonckt, 2011) start by modelling an high level dialogue between the user and an interactive system and then refine such models following a stepwise procedure, usually in order to obtain a running system. For example, the CAMELEON reference model[5], which can be defined as a generative model, includes the following steps: domain/task models, abstract user interface,

[5] `https://www.w3.org/community/uad/wiki/Cameleon_Reference_Framework`

concrete user interface, final user interface. The UpRISE model has not been developed according the model-based paradigm first of all because this paradigm is focused at describing and then generating an interactive system as a whole, while we wanted to focus on user's reactions without having to consider all the aspects of an interactive system. More specifically the meta-modeling of the task proposed in CAMELEON show some limitation with respect to what we would like to describe (as detailed below), and allows to model all the tasks according to the vision of the CTT meta-model. However we can think of future integrations in this model, especially in the generative aspects that make it particularly interesting from our point of view since lead at the generation of a concrete interface.

In Figures 1, 2, 3, 4 we exemplify how the models we discussed so far could be used to represent a situation which falls in the scope of UpRISE, i.e., when a user wants to positively react to a product they have purchased from Amazon[6], with the aim of highlighting their limits with regards to our goals and their differences in comparison with UpRISE. For each model, we summarize its type (e.g., descriptive), object/domain and whether it is applicable to intelligent interactive systems (ISS for short). If so, we represent the aforementioned situation in terms of the model in question and comment on limits and differences in the "notes" box.

<table>
<tr><th>Name</th><th>Type/goal</th><th>Object</th><th>Applicable to IIS?</th></tr>
<tr><td>KAM</td><td>descriptive</td><td>Keyboard keys</td><td>NO
(different domain)</td></tr>
<tr><td>3-state model</td><td>descriptive</td><td>Operation of pointing devices</td><td>NO
(different domain)</td></tr>
<tr><td>UAN</td><td>descriptive</td><td>Interfaces</td><td>YES</td></tr>
<tr><td colspan="2">Example</td><td colspan="2"><u>Task:</u> express a five-star rating
<table>
<tr><td>user actions</td><td>interface feedback</td></tr>
<tr><td>(1, 2) ~[5th_star_icon]Mv
(4) M^</td><td>(3) 5th_star_icon!
(5, 6) ∀star_icon: star_icon!! & display("sent")</td></tr>
</table>

(1) Move the cursor to the fifth star icon
(2) Depress the mouse button and (3) the icon will be highlighted (red border)
(4) Release the mouse button and (5) all five star icons will be highlighted (colour filling). (6) A success message will be displayed
</td></tr>
<tr><td colspan="2">Notes</td><td colspan="2">The UAN model can describe the physical actions performed by the user, however, it is too fine grained for our purposes. The description is not able to grasp the high level interconnections between the filling of a review and its meaning for the system. The final representation would be scarcely intuitive and in general not expressive enough.</td></tr>
<tr><td>Instrumental interaction</td><td>descriptive</td><td>Interfaces</td><td>YES</td></tr>
<tr><td colspan="2">Example</td><td colspan="2">Products can be understood as domain objects, i.e., objects of interest. The only attribute of domain objects users can manipulate is their rating (in our terms, users can express reactions). To do so, they use widgets (e.g., a five-star rating scale) as interaction instruments, i.e., mediators between users and domain objects. When users click on the fifth star icon, they carry out an action on the interaction instrument, which fires a command- storing a new rating for a "user"-"domain object" pair. The interaction instrument provides an immediate reaction to the user's action by highlighting the border of the selected icon. When the command is executed, the interaction instrument provides further feedback by filling in with colour all five stars.
Widgets can also be understood as a reification of the "rating" attribute and of the store new rating command. If we consider products as domain objects, widgets have a medium to large spatial offset (i.e., the distance between the logical part of the instrument and the object it operates on), while they have a null spatial offset if we consider the reified "rating" attribute as the domain object.</td></tr>
</table>

Figure 1. Use of existing HCI models to represent users reacting to a purchased product in Amazon - part 1

[6]In our examples, we will assume that users are currently viewing the "product review page", where all the relevant widgets are available

	Notes	The instrumental interaction model specifically focuses on user interfaces and, in particular, on domain objects and interaction instruments, thus leaving the description of the interaction flow at a more general level out of its scope. For example, providing a rating also activates feedback which is decoupled from the interaction instrument and thus not represented in this model: firstly, a success message is displayed, secondly, personalized product recommendations can be generated.	
GOMS	predictive	Task performance	YES
	Example	- GOAL: react to a purchased product - OPERATORS: perceptual, motor or cognitive acts used to achieve stated goal (an example will be provided in the following, with regard to KLM) - METHODS: (1) use five-star rating scale; (2) use textarea - SELECTION RULES: use method 1 if user wants to provide a quantitative reaction or if user has little time; use method 2 if user wants to provide a qualitative reaction or if user has no time constraints	
	Notes	The model is conceived for describing merely the puntual interaction, not considering what can happen after (recommendation, feedback) and focusing only on user actions. It is suitable for measuring user performances with different tasks and for the comparison of alternative courses of action.	
KLM (GOMS family)	predictive	Task performance	YES
	Example	Operator sequence for method "use five-star rating scale (goal: react to a purchased product)" 1) initiate the reaction process (M) - 1.35 sec 2) find the five-star widget (M) - 1.35 sec 3) point to the fifth star icon (P) - 1.1 sec 4) press mouse button (B) – 1 sec 5) release mouse button (B) – 1 sec 6) point to original position (P) - 1.1 sec Assumption: user has their hand on their mouse TOTAL TIME: 2M + 2P + 2B = 2*1.35 + 2*1.1 + 2*1 = 6.9 sec Time estimates are based on: Card, Stuart K; Moran, Thomas P; Newell, Allen (1980). "The keystroke-level model for user performance time with interactive systems". Communications of the ACM. 23 (7): 399.	
	Notes	The KLM model focuses on the very specific details of the interaction between the human and the system, focusing in particular on user actions. Here, the time estimates are crucial, while for our model they are unnecessary and even detrimental since they shift the focus from the high level to the more physical description of the interaction.	
Seven Stages of Action	descriptive + predictive	Human behaviour	YES

Figure 2. Use of existing HCI models to represent users reacting to a purchased product in Amazon - part 2

	Example	1. Forming the goal: user wants to positively react to a product they purchased. 2. Forming the intention: user decides to use the five-star widget to express the top rating (five stars) 3. Specifying an action: User decides to use their mouse to point to the five star widget and to press the mouse button to select the fifth star 4. Executing the action: user physically executes the previously specified actions 5. Perceiving the state of the world: user perceives that all five stars are now filled in with colour and a "sent" message is displayed 6. Interpreting the state of the world: user interprets their perception and assumes that it corresponds to a five-star rating; they also assume that their rating was sent to the system. 7. Evaluating the outcome: user understands that their action was successful and they reached their goal. No further planning is needed. As far as the gulf of execution is concerned, user might find that the granularity provided by the available widget matches their needs (or not); they might also find that the widget is difficult or easy to operate, e.g. because of icon size. As far as the gulf of evaluation is concerned, user might find the resulting state of the widget difficult or easy to perceive, e.g. because of colour contrast between icons and their background.	
	Notes	This model analyses how a specific goal is satisfied through a sequence of well-planned user actions. Differently from our model, interaction is always initiated by a user. In addition, modifications in the state of the world which may be enacted and therefore, perceived at a later time (e.g., generation of personalized recommendations) are not taken into account. The focus is on usability. In addition, this model is very general and does not provide a specific vocabulary to describe interface components and actions.	
Interaction framework		Human/system interaction	YES
	Example	Steps in the interaction cycle: 1. the user formulates the goal and a task to achieve that goal: user wants to positively react to a product they purchased and decides to use the five-star widget to express the top rating (five stars) 2. the interface translates the input language into the core language: user's selection of the fifth star is translated into a positive rating (5 out of 5) for a certain product 3. the system transforms itself into a new state: the system stores user's reaction and is therefore aware of their feelings with regards to a certain product 4. the system renders the new state in the output language and sends it to the user: the system updates the visual appearance of the five-star widget (all icons are filled in with color) and displays a "sent" message. Translation steps: 1. articulation: user articulates the task through a sequence of actions which target the five-star widget (e.g., pointing the widget, selecting the fifth icon, ...) 2. performance: user's rating is used to update the system knowledge base. 3. presentation: system knowledge on user's feelings with regards to a certain product is presented by means of a conveniently colored five-star widget 4. observation: observing the system output, user understands that system has acquired their reaction to the current product.	
	Notes	Similarly to the Seven Stages of Action, this model analyses how a specific goal is satisfied through a sequence of well-planned user actions, and the user always plays an active role. In addition, this model is also very general and does not provide a specific vocabulary to describe interface components and actions, while the focus is on translation steps. Modifications in the state of the world which are enacted at a later	

Figure 3. Use of existing HCI models to represent users reacting to a purchased product in Amazon - part 3

		time (e.g., generation of personalized product recommendations) are not taken into account.	
Model-based user interface	*Generative*	Human/system interaction	YES
Example (https://www.w3.org/community/uad/wiki/Cameleon_Reference_Framework)		1. *domain models*: These focus on the information handled by the application. One approach to representing domain models is with UML diagrams, so that the e-commerce domain and related concepts could be represented using this well-known notation. 2. *task models*: These describe the tasks that the user and the system carry out to achieve the application's objectives without getting distracted by the details of the user interface. A meta-model for tasks based upon the ConcurTaskTrees (CTT) notation is available as a Working Draft from the MBUI Working Group. According to CTT classical task representation, there are not tasks that are specific for our example, but the meta-model gives the possibility of adding task types. The closer ones are: Overview (System Tasks); Single Selection (Interaction Tasks); Comparing (User Tasks). 3. *abstract user interface*: These are models of the user interface that are independent of the choice of platform and of the modes of interaction (visual, aural, tactile). According to the MBUI - Abstract User Interface Models, the user reaction could be described in general terms of InteractionEvent -> SelectionEvent, in the AbstractInteractionUnit composed by a PresentationSupport, an EventSupport. 4. *concrete user interface*: These model the user interface for a given platform, e.g. desktop PC, tablet, smartphone, connected TV and so forth. Here we could specify more in detail that the user is reading a product review web page for desktop and interacts with a 5-star rating scale widget for providing feedback on a product, on a vertical page template. These steps could be done in a more formal way by using the Model-based Language for Interactive Applications Environment (MARIAE). 5. *final user interface*: These are created for a specific class of device. The Final User Interface is generally created automatically by the authoring tool, taking into account the user interface skins selected by the designer for the specific device. In our example the web page could be automatically generated (by MARIA) using HTML5 and CSS3, selecting the final UI template.	
Notes		The meta model ConcurTaskTrees (CTT) for modeling user/system/interaction and abstract tasks offers limited possibilities with respect to our goals in terms of formal description of the tasks. For example User Tasks are limited to Problem Solving, Comparing, Planning and Interaction tasks do not consider any kind of reaction. Additional task types may be used for added flexibility. *Notice that the above definitions are quoted from the Cameleon Reference Framework official web page.*	

Figure 4. Use of existing HCI models to represent users reacting to a purchased product in Amazon - part 4

4. The UpRISE model

The UpRISE model aims at the formal description of the dialogue among systems and users that are willing to react to the system behaviour. As detailed in Section 3, formalisms are useful also in the HCI domain since they give the analyst a deeper understanding of the system being studied and are able to represent things in such a way that the representation can be analyzed and manipulated without regard to the meaning (Dix, 2003), and they can simulate behavior without the need of a running system.

In order to properly describe interaction we need to take into account the two actors involved in this exchange, i.e., the system and the user, as well as the actions they carry out to ask for reactions, provide reactions and eventually offer further contents as a sort of "response" to user reactions. Furthermore, we need to consider the objects of user reactions (for example, photos and videos), as well as the means used to express reactions themselves, for example heart-shape widgets that allow to bookmark users' favourite contents or textareas used to input free comments.

In the following, we will introduce our formal notation (Section 4.1) and describe the model in detail (Section 4.2).

4.1. Formalisms

Table 1 introduces the formal notation we will use to describe the UpRISE model, mainly based on the set theory.

Main sets: actors, items, operations A is s set of actors; $a \in A$ is a generic actor. I is a set of items; $i \in I$ is a generic item. O is a set of operations; $o \in O$ is a generic operation.	A**, the actors set** $A = S \cup U$ $S \subseteq A$ is a set of systems; $s \in S$ is a system. $U \subseteq A$ is a set of users; $u \in U$ is a user.
I**, the items set** $I = OB \cup WI \cup RS$ $OB \subseteq I$ is a set of objects; $ob \in OB$ is an object. $WI \subseteq I$ is a set of widgets; $wi \in WI$ is a widget. $RS \subseteq I$ is a set of responses; $rs \in RS$ is a response.	O**, the operations set** $O = ARC \cup PRC \cup PRS$ $ARC \subseteq O$ is a set of "system asks reaction" operations; $arc \in ARC$ is a "system asks reaction" operation. $PRC \subseteq O$ is a set of "user provides reaction" operations; $prc \in PRC$ is a "user provides reaction" operation. $PRS \subseteq O$ is a set of "system provides response" operations; $prs \in PRS$ is a "system provides response" operation.

Table 1. UpRISE formal notation

In UpRISE, functions are presented in the form $F : X \rightarrow Y$, where F is the name of the function, X is its *domain*, i.e., the set of input values for which F is defined, and Y is its *codomain*, i.e., the set into which the output of F is constrained to fall.
The notation $\mathcal{P}(X)$ denotes the power set of set X, i.e., the set of all subsets of X, including the empty set and X itself.

4.2. Model description

UpRISE is organized in three different categories of elements -actors, items and operations- each cooperating in the definition of the system (Figure 5). Every instance of these elements is then further specified by a list of parameters, having a definite domain. Formally, we can define an UpRISE model as follows:

Definition 4.1. An UpRISE model m is a tuple $< s, u, I, O >$ where $s \in S \subseteq A$ is the system, $u \in U \subseteq A$ is the user, I is a set of items, O is a set of operations.

In this section we will describe UpRISE and its features.

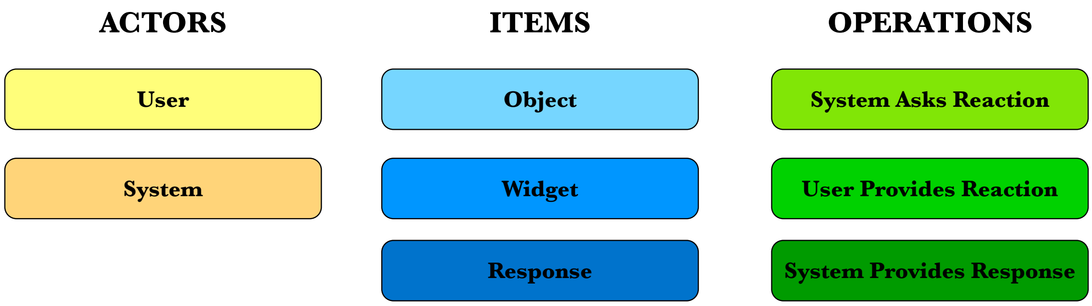


Figure 5. Overview of UpRISE.

4.2.1. Actors

An Actor $a \in A$ is, in general, an entity that is able to perform actions towards other actors. We formally define A as follows:

Definition 4.2. (Actors)
$A = \{x|x$ can act upon an environment$\}$
$A = S \cup U$

where $S \subseteq A$ is a set of *Systems* and $U \subseteq A$ is a set of *Users* (Figure 6).

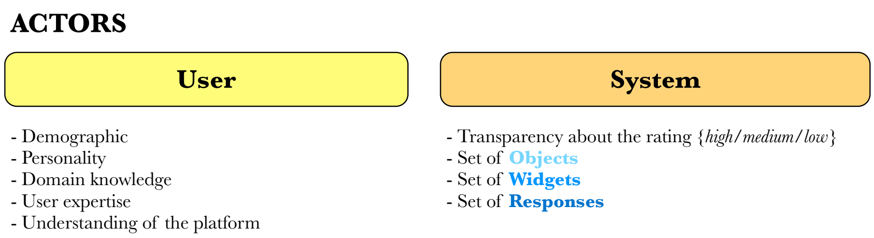


Figure 6. The Actors of the UpRISE.

4.2.2. System

In UpRISE, a system $s \in S$ is represented as an Actor that can be characterized through the following functions:

- $systemHasTransparency : S \to \{high, medium, low\}$.
  A system can be more or less transparent about its use of reactions. In particular, is the process that takes into account the reaction shown as a black box to the user, or does the system provide visibility and/or the ability to tune it in any way? Let us take the case of a recommender system as an example: the mere explanation of the use of user ratings can be considered as medium level of transparency. However, if the system offers the possibility of recommendation adjustment (e.g., it asks users to evaluate previous or possible future recommendations), it can be considered high, see (Cramer et al., 2008). Clearly, this feature is related to some of the features of the user: a higher transparency on the part of the system can greatly improve the users' understanding of the platform.
- $systemHasObjects : S \to \mathcal{P}(OB)$.
  This function links the system to a set of Objects $OB \subseteq I$ (see Section 4.2.4).

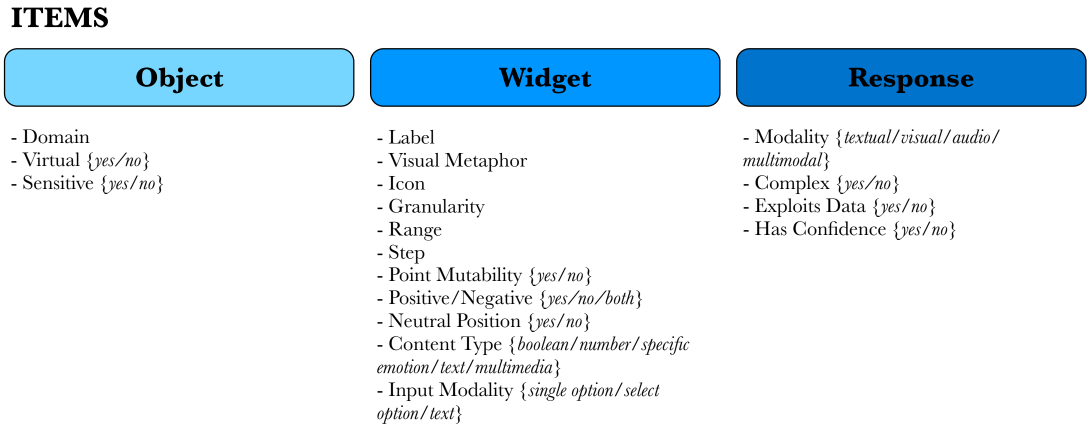


Figure 7. The Items of the UpRISE.

- $systemHasWidgets : S \rightarrow \mathcal{P}(WI)$.
  This function links the system to a set of Objects $WI \subseteq I$ (see Section 4.2.4).
- $systemHasResponses : S \rightarrow \mathcal{P}(RS)$.
  This function links the system to a set of Objects $RS \subseteq I$ (see Section 4.2.4).

4.2.3. User

In UpRISE, a user $u \in U$ is represented as an Actor. The peculiarities regarding the users that interact with a certain system do not constitute a proper feature of the system *per se*, but can however offer an important interpretation factor when we are interested in understanding the type of interactions provided by the system. In a design-oriented perspective, users represent the target of the system, and knowing "who they are" is important because their preferences, habits, needs and features will inform all decisions on system design. Users can be defined upon features such as their demographics, personality, domain knowledge, expertise and understanding of the platform. However, the user modeling is out of the scope of this paper.

4.2.4. Items

The second key component of the UpRISE model are *Items* (Figure 7). An item $i \in I$ can be thought as the information content brought via the system s to the user u. We formally define I as follows:

Definition 4.3. (Items)
$I = \{x | x \textit{ is a tool or a piece of information provided by a system } s \textit{ to a user } u\}$
$I = OB \cup WI \cup RS$

where $OB \subseteq I$ is a set of *Objects*, $WI \subseteq I$ is a set of *Widgets*, and $RS \subseteq I$ is a set of *Responses*

4.2.5. Object

An *Object* $ob \in OB$ is the atomic entity that the user u benefits from the system s. Also, the system can present objects to users when it provides them with recommendations, that are a specific form of response rs. Users express their reactions r with respect to objects. An Object can be characterized through the following functions:

- $objectHasDomain : OB \rightarrow \{x | x \textit{ is a domain, a sector or an area of interest}\}$.
  The domain of an Object is the content of the object, such as movies, books, etc.
- $objectIsVirtual : OB \rightarrow \{yes, no\}$.
  The type of an Object can be virtual (such as a movie or a notification that one user befriended another) or tangible (such as a real life object like a hoover).
- $objectHasSensitivity : OB \rightarrow \{yes, no\}$.

An object can be sensitive, i.e. convey personal and sensitive information (such as a post with political views, sexual orientation and so on.)

4.2.6. Widget

A *Widget* $wi \in WI$ is the interface control that allows users to express their reactions r. Widgets can hugely affect the evaluation of Objects, and therefore their features must be accounted for. Our representation of Widgets builds on the studies conducted in (Cena & Vernero, 2015). A Widget can be characterized through the following functions:

- $widgetHasLabel : WI \rightarrow \{yes, no, not\ applicable\}$.
  Verbal cues, such as text or numbers, can be added to a point in a widget in the form of labels.
- $widgetHasVisualMetaphor : WI \rightarrow \{x|x\ is\ a\ visual\ metaphor\} \cup \{none\}$.
  Not all widgets make use of metaphors in their visual presentation forms. Visual metaphors can impact on the widget interpretation and emotional connotation. Examples of visual metaphors are “human”, “technical” and “neutral”.
- $widgetHasIcon : WI \rightarrow \{x|x\ is\ an\ icon\} \cup \{none\}$.
  An icon is the specific image or presentation form used in a rating scale.
- $widgetHasGranularity : WI \rightarrow \mathbb{N} \cup \{not\ applicable\}$.
  Granularity represents the number of positions offered by a widget.
- $widgetHasRange : WI \rightarrow \{< min, max > |min \in \mathbb{Q}; max \in \mathbb{Q}; min \leq max\} \cup \{not\ applicable\}$.
  The range represents the minimum and maximum values of the widget (e.g. from 0 to 10). It is not applicable to widgets which allow to express emotions.
- $widgetHasStep : WI \rightarrow \mathbb{Q} \cup \{not\ applicable\}$.
  The step represents the distance between two points in a widget. It is not applicable to widgets which allow to express emotions or which only offer a single point.
- $widgetHasPointMutability : WI \rightarrow \{yes, no\} \cup \{not\ applicable\}$.
  Point mutability indicates whether all points in a widget are represented in the same way or not.
- $widgetHasPositiveNegative : WI \rightarrow \{positive, negative, both\} \cup \{not\ applicable\}$.
  The positive/negative feature indicates the presence of either only positive, or only negative, or both kinds of points.
- $widgetHasNeutralPosition : WI \rightarrow \{yes, no\} \cup \{not\ applicable\}$.
  Neutral reactions can be allowed by widgets offering an intermediate or middle point.
- $widgetHasContentType : WI \rightarrow \{boolean,\ number,\ emotion,\ text,\ multimedia\}$.
  Depending on its type, a widget can allow to express a generic approval (represented through a boolean), an evaluation (which can be somehow expressed in the form of a number), a specific emotion, any type of reaction through free or pre-defined text, or multimedia content.
- $widgetHasInputModality : WI \rightarrow \{single\ option,\ select\ option,\ text\}$.
  A widget can allow to simply select one of a set of options or allow to freely provide a textual input through free text.

4.2.7. Response

A *Response* $rs \in RS$ is any kind of content a system s provides to a user u after or in consequence of the fact that they have provided some reaction r. The form in which the Response is generated can vary a lot, depending on its nature and the type of system that generates it. The features of a Response are modeled through the following functions:

- $responseHasModality : RS \rightarrow \{textual,\ visual,\ audio,\ multimodal\}$.
  The modality of a Response can vary; it can be textual, visual, audio, or multimodal if it involves more than one modality.
- $responseIsComplex : RS \rightarrow \{yes,\ no\}$.
  The complexity of a Response is defined upon the kind of content that the Response itself provides. If we take in consideration for instance a recommender system, a simple acknowledgement of user actions or a textual explanation following a reaction can be considered as a simple Response, while the recommendation of an object can be considered as a complex Response.
- $responseExploitsData : RS \rightarrow \{yes,\ no\}$.
  The value of the data exploitation parameter depends on the fact that a Response is generated by making

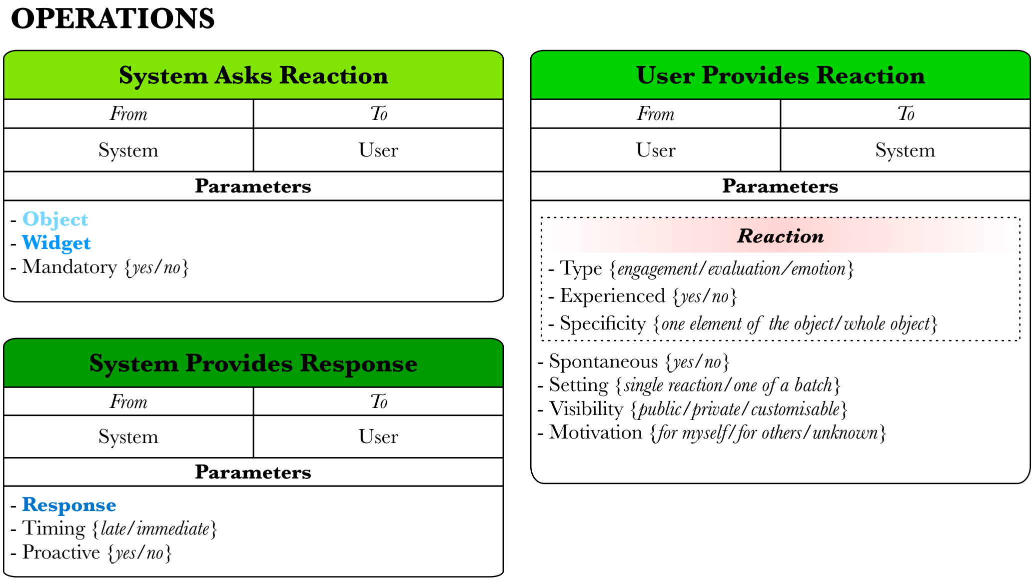


Figure 8. The Operations of the UpRISE.

use of data that the system has about the user. For instance, a system that provides an acknowledgement after a Reaction such as "Your rating has been registered" doesn't exploit data.

- $responseHasConfidence : RS \rightarrow \{yes,\ no\}$.
  In the case of recommender systems, a Response can be accompanied by a numerical value that indicates how confident the system is in the goodness of its prediction.

Notice that a Response can also represent feedback as it is usually intended in the Human-Computer Interaction domain, i.e., feedback which simply acknowledges the successful or unsuccessful outcome of a user action (in this case, for example, the fact that a reaction was correctly received). System designers should pay attention to providing appropriate and timely feedback to guarantee a successful user experience.

4.2.8. Operations

Operations are the third and final component of the UpRISE model (Figure 8). An operation $o \in O$ allows to illustrate what kind of interactions occur between the system s and the user u. We formally define O as follows:

Definition 4.4. (Operations)
$O = \{x | x \text{ is an action involving a reaction } r\}$
$O = ARC \cup PRC \cup PRS$

where ARC is a set of "system asks reaction" operations, PRC is a set of "user provides reaction" operations, and PRS is a set of "system provides response" operations.

Each operation is modelled as a function, while the subject that performs the operation is referenced in the name of the function itself.

4.2.9. System Asks Reaction.

The *System Asks Reaction* $arc \in ARC \subseteq O$ operation is performed by the system and it is directed to the user. A "system asks reaction" operation arc is represented as a function $U \rightarrow OB * WI$ that illustrates how, given a certain user u, the system s can ask for a reaction by providing a widget wi (e.g. rating scale) for the encoding of the reaction itself and an object ob that has to be reacted upon.
Additionally, the *System Asks Reaction* operation can be characterized through the following function:

- $operationIsMandatory : ARC \rightarrow \{yes,\ no\}$.

The *Ask Reaction* operation can be can mandatory or optional. A mandatory *Ask Reaction* would block the user until the reaction is provided.

4.2.10. User Provides Reaction

The *User Provides Reaction* $prc \in PRC \subseteq O$ operation is the most relevant operation implemented in UpRISE. Formally, a "user provides reaction" operation prc is represented as a function $S{*}OB{*}WI \rightarrow R$ that illustrates how the user u provides a reaction r for a certain object ob by means of a widget wi in the context of a certain system s.
The most important parameter is the reaction r, a complex element which can refer to either: *i)* an expression of engagement *ii)* an evaluation *iii)* or an emotion and can be modeled through the following functions:

- $reactionHasType : R \rightarrow \{engagement, evaluation, emotion\}$.
  The purpose of this field is to express which kind of reaction the user is providing to the system.
- $reactionIsExperienced : R \rightarrow \{yes,\ no\}$.
  The purpose of this feature is to represent if users either experienced a certain Object or not. For instance, users could positively rate a movie because they are expecting it to be great or because they have seen it and they like it. It can be noted that some systems could actually enforce the experienced condition. For instance, in Amazon, users can rate an item only if they actually purchased it.
- $reactionHasSpecificity : R \rightarrow \{to\ one\ element\ of\ the\ object,\ to\ the\ whole\ object\}$.
  User reactions could concern either a specific part of an object (for example, an actor in a movie) or the object as a whole (the whole movie).

The other parameters of the "user provides reaction" operation can be modeled through the following functions:

- $operationIsSpontaneous : PRC \rightarrow \{yes,\ no\}$.
  This feature is directly connected to the mandatory feature of the *System Asks Reaction* operation: are users providing a reaction spontaneously, or are they forced to do so?
- $operationHasSetting : PRC \rightarrow \{single\ reaction,\ one\ of\ a\ batch\}$.
  The user can provide an atomic, single reaction or one of a batch. Providing a reaction as part of a batch can change users' judgment: for example, users could be inclined to compare the objects rather then evaluate each single object by itself.
- $operationHasSocialContext : PRC \rightarrow \{yes,\ no\}$.
  Providing a reaction in a social context, where it is possible to see the reactions of the other users, can have an effect on users' judgment.
- $operationHasVisibility : PRC \rightarrow \{private,\ public,\ custom\}$.
  The fact that a reaction is public, private or custom (i.e., visibility is limited to a selected group of contacts) could impact user attitudes during the evaluation. This aspect is strongly related to the *objectHasSensitivity* function that characterizes objects.
- $operationHasMotivation : PRC \rightarrow \{for\ myself,\ for\ others,\ unknown\}$.
  The motivations behind a rating would be a fundamental aspect to be taken into account but it is not always possible to know the real user motivations. Thus, we focus on goal and motivation of the system, e.g. to share opinions or to consume personalised contents. This is also related to the *operationHasVisibility* function.

4.2.11. System Provides Response

The *System Provides Response* $prs \in PRS \subseteq O$ operation is represented as a function $U * R \rightarrow RS$ that illustrates how the system s can provide a response RS, given a user u and a reaction r on their part. The parameters that characterize this operation are:

- $operationHasTiming : PRS \rightarrow \{late,\ immediate\}$.
  This function roughly defines the amount of time that elapsed between the user Reaction and the provided Response, distinguishing between "late" and "immediate".
- $operationIsProactive : PRS \rightarrow \{yes,\ no\}$.
  This function encodes whether the Response is given spontaneously by the system or if it is triggered by a user action.

5. UpRISE as a descriptive tool

The first purpose of UpRISE model is to provide a descriptive tool to analyze existing systems. As described in Carroll (2003), models are a simplification of the reality useful for understanding the behavior of a complex artifact as an interactive systems. Models can be usually described as either *descriptive*, *predictive* or *generative*: descriptive models should have the ability to represent (all the aspects of) a phenomenon, predictive models should have the ability to anticipate behavior, while generative models should have the ability to imagine new solutions to a problem.

In this section, we aim at showing how UpRISE can be used as a descriptive model, able to analyse real life interactive intelligent systems. This can be seen also as a validation of the expressive power of the model. To this aim, we chose six of the most popular interactive social systems on the web, of different types (e-commerce, media provider, social network) and exploiting different widgets (emoticons, textboxes, rating scales,...), all using reactions to provide a personalized response to users, such as a personalized selection of content or explicit suggestions. We chose these systems since we think that they are representative of the different categories of interactive systems. In Table 2 we summarize their different features. In this section, we present the description of two representative systems: Netflix and Amazon, while the descriptions of the other systems are presented in the Appendix.

	domain	**medium**	**widget**	**object**
Netflix	media provider	movies	rating scale	movies
Amazon	e-commerce	text and pictures	rating scale	products
YouTube	media provider	videos	rating scale	videos/channels
Twitter	social network	text	rating scale	people to follow
Instagram	social network	pictures	rating scale	people to follow
Facebook	social network	text, pictures and videos	emoticon, text	posts and people

Table 2. A selection of popular interactive systems making use of user reactions.

For each system, we first demonstrate how the formal notation we introduced in Section 4 can be used (for Netflix, Sec. 5.1.1 and Amazon, Sec. 5.2.1). Then, for legibility reasons, we provide a more user-friendly description, presenting each system via a group of pictures that show the instantiated model (Sections 5.1.2 and 5.2.2)[7]. Each box is color coded and represents an element of the model (which can be read in the top right corner). Labels of the element fields have been shortened in order to make the pictures more readable (e.g., *HasIcon* is indicated as *icon*). The *System Asks Reaction* boxes are also enriched with the screenshots of the adopted widget.

[7]Note that in both cases we will not provide the exact description of the actor "User", but rather discuss how the features of a given system can target certain types of users. The reason behind this choice is the fact that it is very difficult -from an external point of view- to describe the typical user of a system.

5.1. Netflix

Netflix is a media-services provider which offers a subscription-based streaming service involving a vast library of movies and television programs, some of which are produced in-house.

5.1.1. System description according to UpRISE formal notation

A formal description of Netflix is provided in the following.

ACTORS	
System	
Netflix	systemHasTransparency(Netflix) = medium systemHasObjects(Netflix) = Content systemHasWidgets(Netflix) = Thumbs systemHasResponses(Netflix) = Recommendation, Match Percentage
User	
...	[A detailed description of the user is not provided, see Section 4.2.3]
ITEMS	
Object	
Content	objectHasDomain(Content) = movies, TV series, documentaries objectIsVirtual(Content) = yes objectHasSensitivity(Content) = no
Widget	
Thumbs	widgetHasLabel(Thumbs) = no widgetHasVisualMetaphor(Thumbs) = human widgetHasIcon(Thumbs) = thumbs up, thumbs down widgetHasGranularity(Thumbs) = 2 widgetHasRange(Thumbs) = *not applicable* widgetHasStep(Thumbs) = *not applicable* widgetHasPointMutability(Thumbs) = no widgetHasPositiveNegative(Thumbs) = both widgetHasNeutralPosition(Thumbs) = no widgetHasContentType(Thumbs) = boolean widgetHasInputModality(Thumbs) = select option
Response	
Recommendation	responseHasModality(Recommendation) = textual responseIsComplex(Recommendation) = yes responseExploitsData(Recommendation) = yes responseHasConfidence(Recommendation) = no
Match Percentage	responseHasModality(Match Percentage) = textual responseIsComplex(Match Percentage) = yes responseExploitsData(Match Percentage) = yes responseHasConfidence(Match Percentage) = yes
OPERATIONS	
System Asks Reaction	
At Registration	OB = {Content} WI = {simple selection} operationIsMandatory(At Registration) = yes
Evaluate	OB = {Content} WI = {Thumbs} operationIsMandatory(Evaluate) = no
User Provides Reaction	
At Registration	R = { reactionHasType(At Registration) = evaluation reactionIsExperienced(At Registration) = yes reactionHasSpecificity(At Registration) = to the whole object

	}
	operationIsSpontaneous(At Registration) = no
	operationHasSetting(At Registration) = one of a batch
	operationHasSocialContext(At Registration) = no
	operationHasVisibility(At Registration) = private
	operationHasMotivation(At Registration) = for myself
Evaluate	R = {
	reactionHasType(At Registration) = evaluation
	reactionIsExperienced(At Registration) = yes
	reactionHasSpecificity(At Registration) = to the whole object
	}
	operationIsSpontaneous(Evaluate) = yes
	operationHasSetting(Evaluate) = single reaction
	operationHasSocialContext(Evaluate) = no
	operationHasVisibility(Evaluate) = private
	operationHasMotivation(Evaluate) = for myself
System Provides Response	
Recommendation	RS = {Recommendation}
	operationHasTiming(Recommendation) = late
	operationIsProactive(Recommendation) = yes
Match Percentage	RS = {Match Percentage}
	operationHasTiming(Match Percentage) = late
	operationIsProactive(Match Percentage) = yes

5.1.2. Visual system description

In terms of the UpRISE framework, Netflix manages only one type of object, i.e, video contents such as movies, TV series and documentaries (Figure 9 "Content" box).

At the sign up, the system explains why reactions are important and why it is asking for them. However, the system does not provide any further explanation at a later time. Therefore, we consider the system transparency as "medium" (Figure 9, "Netflix" box).

All reactions are expressed through a single widget, i.e., a thumbs up/thumbs down rating scale (Figure 9, "Thumbs" box).

As for responses, Netflix offers both recommendations (Figure 9, "Recommendation" box) and "match percentages" (Figure 9, "Match Percentage box") Recommendations are shown in the homepage, and they are based on previously viewed or rated content. Recommendations are enriched with some text explaining why the system generated such suggestions. Match percentage responses, on the contrary, are shown with every object and represent an attempt to estimate the level of user interests with respect to the current object.

Finally, Netflix offers two implementations for each type of operation. As far as "system asks reaction" operations are concerned, "at registration" requests users to react with a "thumbs up" to 3 objects in a list during the registration phase (Figure 10, "System Asks Reaction: At Registration" box), while "evaluate" represents a general request of expressing a reaction that can be applied to any object (Figure 10, "System Asks Reaction: Evaluate" box). The two "user provides reaction" operations closely match the "system asks reaction" operations (Figure 10, "User Provides Reaction: At Registration" box and "User Provides Reaction: Evaluate" box). The two "system provides response" operations correspond to the two response types presented in Figure 9. In fact, we have a "recommendation" (Figure 10), "System Provides Response: Recommendation" box) and a "match percentage" operation (Figure 10, "System Provides Response: Match Percentage" box).

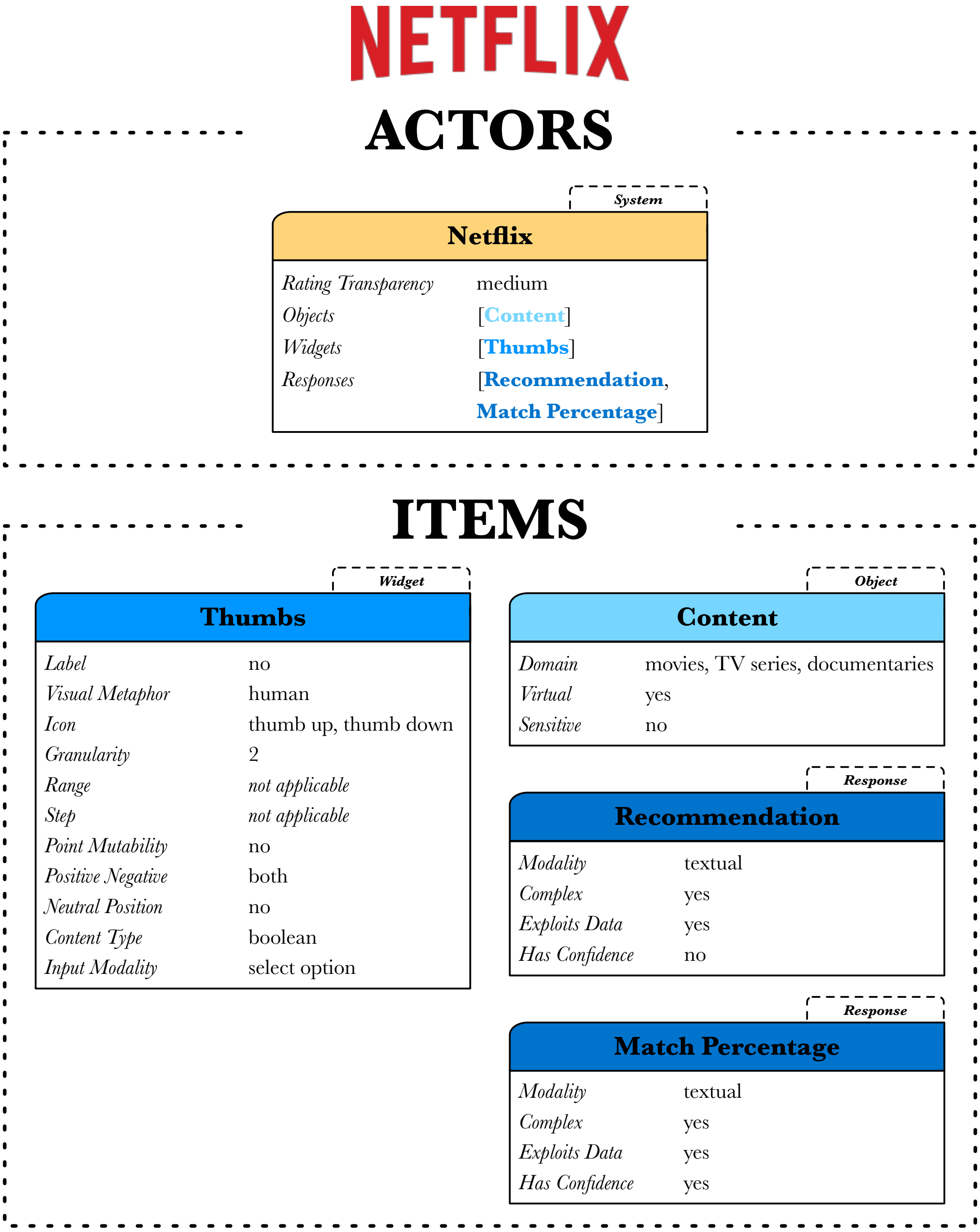


Figure 9. Netflix representation according to the UpRISE model: *actors* and *items*.

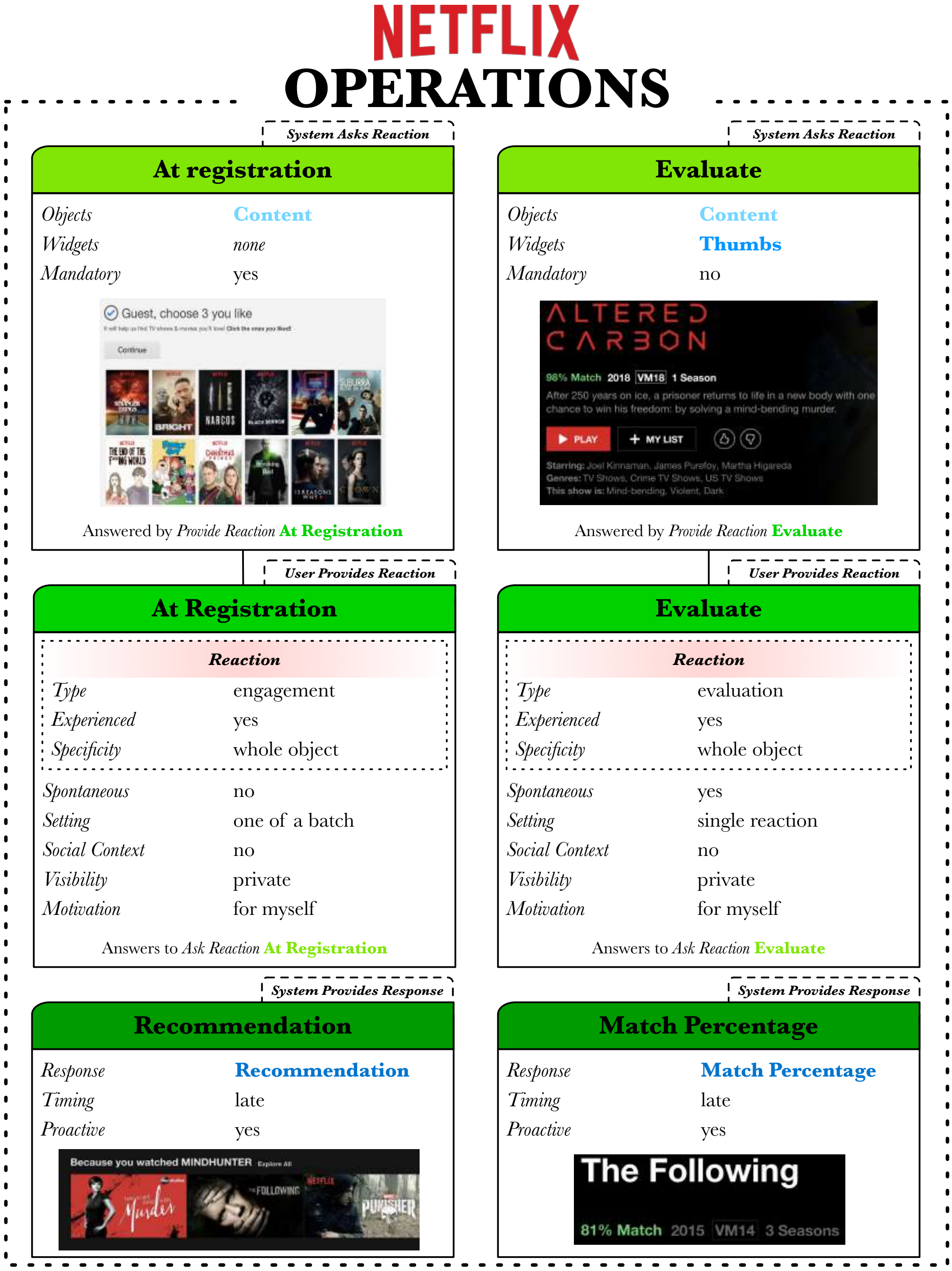


Figure 10. Netflix representation according to the UpRISE model: *operations*.

5.2. Amazon

Amazon is one of the widest successful e-commerce platform that sells practically all types of goods and products all around the world.

5.2.1. System description according to UpRISE formal notation

A formal description of Amazon is provided in the following.

ACTORS	
System	
Amazon	systemHasTransparency(Amazon) = high systemHasObjects(Amazon) = Product, Seller, Packaging systemHasWidgets(Amazon) = Stars (1), Stars (2), Radio buttons, Likert (5 points), Likert (4 points) Textarea (title), Textarea (review) systemHasResponses(Amazon) = On-site recommendation, Email recommendation
User	
...	[A detailed description of the user is not provided, see Section 4.2.3]
ITEMS	
Object	
Product	objectHasDomain(Product) = movies, music & games, books and audible, home, garden and tools, pet supplies, food and groceries, beauty & health toys, kids and baby, electronics, computers & office, clothing, shoes & jewelry, sports & outdoor, automotive & industrial objectIsVirtual(Product) = yes/no objectHasSensitivity(Product) = no
Seller	objectHasDomain(Seller) = seller (human) objectIsVirtual(Seller) = yes objectHasSensitivity(Seller) = no
Packaging	objectHasDomain(Packaging) = seller (human) objectIsVirtual(Packaging) = yes objectHasSensitivity(Packaging) = no
Widget	
Stars (1)	widgetHasLabel(Stars (1)) = yes widgetHasVisualMetaphor(Stars (1)) = neutral widgetHasIcon(Stars (1)) = stars widgetHasGranularity(Stars (1)) = 5 widgetHasRange(Stars (1)) = 1-5 widgetHasStep(Stars (1)) = 1 widgetHasPointMutability(Stars (1)) = no widgetHasPositiveNegative(Stars (1)) = no widgetHasNeutralPosition(Stars (1)) = yes widgetHasContentType(Stars (1)) = number widgetHasInputModality(Stars (1)) = select option
Stars (2)	widgetHasLabel(Stars (2)) = yes widgetHasVisualMetaphor(Stars (1)) = neutral widgetHasIcon(Stars (2)) = stars widgetHasGranularity(Stars (2)) = 5 widgetHasRange(Stars (2)) = 1-5 widgetHasStep(Stars (2)) = 1 widgetHasPointMutability(Stars (2)) = no widgetHasPositiveNegative(Stars (2)) = no

	widgetHasNeutralPosition(Stars (2)) = yes widgetHasContentType(Stars (2)) = number widgetHasInputModality(Stars (2)) = select option
Likert (5 points)	widgetHasLabel(Likert (5 points)) = yes widgetHasVisualMetaphor(Likert (5 points)) = technical (Likert-like scale) widgetHasIcon(Likert (5 points)) = *not applicable* widgetHasGranularity(Likert (5 points)) = 5 widgetHasRange(Likert (5 points)) = excellent - terrible protection widgetHasStep(Likert (5 points)) = *not applicable* widgetHasPointMutability(Likert (5 points)) = no widgetHasPositiveNegative(Likert (5 points)) = both widgetHasNeutralPosition(Likert (5 points)) = yes widgetHasContentType(Likert (5 points)) = number widgetHasInputModality(Likert (5 points)) = select option
Likert (4 points)	widgetHasLabel(Likert (4 points)) = yes widgetHasVisualMetaphor(Likert (4 points)) = technical (Likert-like scale) widgetHasIcon(Likert (4 points)) = *not applicable* widgetHasGranularity(Likert (4 points)) = 4 widgetHasRange(Likert (4 points)) = too small - wrong size widgetHasStep(Likert (4 points)) = *not applicable* widgetHasPointMutability(Likert (4 points)) = no widgetHasPositiveNegative(Likert (4 points)) = both widgetHasNeutralPosition(Likert (4 points)) = yes widgetHasContentType(Likert (4 points)) = number widgetHasInputModality(Likert (4 points)) = select option
Textarea (title)	widgetHasLabel(Textarea (title)) = *not applicable* widgetHasVisualMetaphor(Textarea (title)) = none widgetHasIcon(Textarea (title)) = none widgetHasGranularity(Textarea (title)) = *not applicable* widgetHasRange(Textarea (title)) = *not applicable* widgetHasStep(Textarea (title)) = *not applicable* widgetHasPointMutability(Textarea (title)) = *not applicable* widgetHasPositiveNegative(Textarea (title)) = *not applicable* widgetHasNeutralPosition(Textarea (title)) = *not applicable* widgetHasContentType(Textarea (title)) = text widgetHasInputModality(Textarea (title)) = text
Textarea (review)	widgetHasLabel(Textarea (review)) = *not applicable* widgetHasVisualMetaphor(Textarea (review)) = none widgetHasIcon(Textarea (review)) = none widgetHasGranularity(Textarea (review)) = *not applicable* widgetHasRange(Textarea (review)) = *not applicable* widgetHasStep(Textarea (review)) = *not applicable* widgetHasPointMutability(Textarea (review)) = *not applicable* widgetHasPositiveNegative(Textarea (review)) = *not applicable* widgetHasNeutralPosition(Textarea (review)) = *not applicable* widgetHasContentType(Textarea (review)) = text widgetHasInputModality(Textarea (review)) = text
Radio buttons	widgetHasLabel(Radio buttons) = yes widgetHasVisualMetaphor(Radio buttons) = *not applicable* widgetHasIcon(Radio buttons) = none widgetHasGranularity(Radio buttons) = 2 or 3 widgetHasRange(Radio buttons) = *not applicable* widgetHasStep(Radio buttons) = *not applicable* widgetHasPointMutability(Radio buttons) = *not applicable* widgetHasPositiveNegative(Radio buttons) = both widgetHasNeutralPosition(Radio buttons) = no widgetHasContentType(Radio buttons) = text widgetHasInputModality(Radio buttons) = select option
Response	
On-site recommendation	responseHasModality(On-site recommendation) = multimodal (textual and visual)

	responseIsComplex(On-site recommendation) = yes responseExploitsData(On-site recommendation) = yes responseHasConfidence(On-site recommendation) = no
Email recommendation	responseHasModality(Email recommendation) = multimodal (textual and visual) responseIsComplex(Email recommendation) = yes responseExploitsData(Email recommendation) = yes responseHasConfidence(Email recommendation) = no
OPERATIONS	
System Asks Reaction	
Review product	OB = {Product} WI = {Stars (1), Textarea (title), Textarea (review)} operationIsMandatory(Review product) = no
Review seller	OB = {Seller} WI = {Stars (2), Radio buttons, Textarea (review)} operationIsMandatory(Review seller) = no
Review packaging protection	OB = {Packaging} WI = {Likert (5 points)} operationIsMandatory(Review packaging protection) = no
Review packaging size	OB = {Packaging} WI = {Likert (4 points)} operationIsMandatory(Review packaging size) = no
User Provides Reaction	

Review product	R = {
	reactionHasType(Review product) = evaluation
	reactionIsExperienced(Review product) = yes or no
	reactionHasSpecificity(Review product) = to the whole object
	}
	operationIsSpontaneous(Review product) = yes
	operationHasSetting(Review product) = single reaction
	operationHasSocialContext(Review product) = no
	operationHasVisibility(Review product) = public
	operationHasMotivation(Review product) = for others

Review seller	R = {
	reactionHasType(Review seller) = evaluation
	reactionIsExperienced(Review seller) = yes
	reactionHasSpecificity(Review seller) = to the whole object
	}
	operationIsSpontaneous(Review seller) = yes
	operationHasSetting(Review seller) = single reaction
	operationHasSocialContext(Review seller) = no
	operationHasVisibility(Review seller) = public
	operationHasMotivation(Review seller) = for others

Review packaging protection	R = {
	reactionHasType(Review packaging protection) = evaluation
	reactionIsExperienced(Review packaging protection) = yes
	reactionHasSpecificity(Review packaging protection) =
	to one element of the object
	}
	operationIsSpontaneous(Review packaging protection) = yes
	operationHasSetting(Review packaging protection) = single reaction
	operationHasSocialContext(Review packaging protection) = no
	operationHasVisibility(Review packaging protection) = private
	operationHasMotivation(Review packaging protection) = for others

Review packaging size	R = {
	reactionHasType(Review packaging size) = evaluation
	reactionIsExperienced(Review packaging size) = yes
	reactionHasSpecificity(Review packaging size) =
	to one element of the object
	}
	operationIsSpontaneous(Review packaging size) = yes
	operationHasSetting(Review packaging size) = single reaction

	operationHasSocialContext(Review packaging size) = no operationHasVisibility(Review packaging size) = private operationHasMotivation(Review packaging size) = for others
System Provides Response	
On-site recommendation	RS = {On-site recommendation} operationHasTiming(On-site recommendation) = immediate operationIsProactive(On-site recommendation) = yes
Email recommendation	RS = {Email recommendation} operationHasTiming(Email recommendation) = late operationIsProactive(Email recommendation) = yes

5.2.2. Visual system description

In Amazon, users can express their reactions for three kinds of objects: the product, the seller and the packaging (Figure 12, "Product", "Seller" and "Packaging" boxes). Differently from most other commercial systems, in Amazon users are allowed to adjust the recommendations they receive. For example, users can provide their reactions for candidate recommendations in the "recommended for you" section (Figure 11(a)), or provide reactions for various categories of items in the "improve your recommendations" section (Figure 11(b)). Therefore, we deem that Amazon has a high level of transparency about its use of reactions (Figure 12, "Amazon" box). Amazon makes use of different types of widgets: among these, we can name e.g. 5-star rating scales, used for rating products (Figure 13, "Stars (1)" box) and sellers (Figure 13, "Stars (2)" box), textareas used for expressing free-text reviews regarding products and sellers (Figure 14, "Textarea (title)" and "Textarea (review)" boxes), radio buttons, used for rating sellers (Figure 14, "Radio buttons" box), as well as 5-point and 4-point Likert scales, used for rating packaging as far as the protection and size aspects are concerned, respectively (Figure 13, "Likert (5-points)" and "Likert (4-points)" boxes).
As for responses, Amazon only offers product recommendations, which are delivered to users both via email and in different sections of the website (Figure 12, "On-site recommendation" and "Email recommendation" boxes).

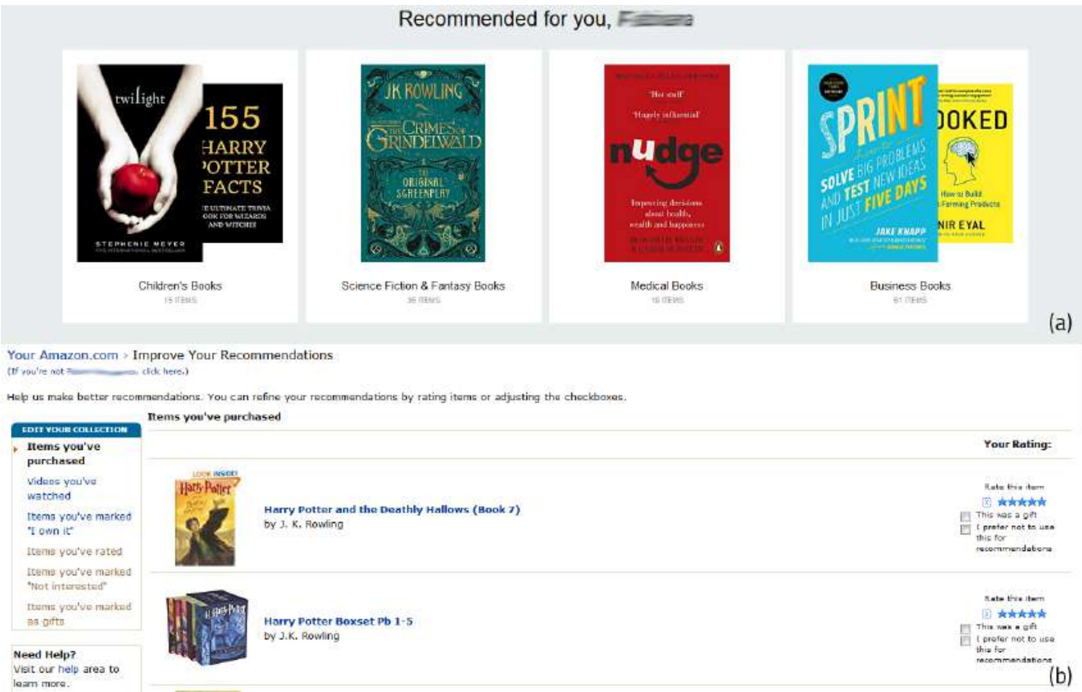


Figure 11. The "Recommended for you" (a) and "Improve your recommendations" (b) sections.

In Amazon, users can freely provide reactions whenever they like. However, they are explicitly prompted to assess their experience after they made a purchase, through the "review product" (Figure 15, "System Asks Reaction: Review product" box) and "review seller" (Figure 15, "System Asks Reaction: Review seller" box) operations. Moreover, users can also provide their reactions for packaging protection and packaging size. The two

“system asks reaction” operations “review packaging protection” and “review packaging size” represent generic requests to review different aspects of packaging that the system does not use in a proactive manner (Figure 16, “System Asks Reaction: Review packaging protection” and “System Asks Reaction: Review packaging size” boxes)
Coherently, there are four types of “user provides reaction” operations, one each for products and sellers and two for packaging (Figure 15, “User Provides Reaction: Review product” and “User Provides Reaction: Review seller” boxes, and Figure 16, “User Provides Reaction: Review packaging protection” and “User Provides Reaction: Review packaging size” boxes).

Finally, there are two types of “system provides response” operations. In fact, recommendations can be delivered either via email (Figure 16, “System Provides Response: On-site Recommendation” box) or on Amazon website (Figure 16, “System Provides Response: Email Recommendation” box).

amazon

ACTORS

System

Amazon

Rating Transparency	high
Objects	[**Product**, **Seller**, **Packaging**]
Widgets	[**Stars (1)**, **Stars (2)**, **Radio buttons**, **Likert (5-points)**, **Likert (4-points)**, **Textarea (title)**, **Textarea (review)**]
Responses	[**On-site Recommendation**, **Email Recommendation**]

ITEMS (p. 1)

Object

Product

Domain	movies, music & games, books and audible, home, garden and tools, pet supplies, food and groceries, beauty & health, toys, kids and baby, electronics, computers & office, clothing, shoes & jewelry, sports & outdoor, automotive & industrial
Virtual	yes and no
Sensitive	no

Object

Seller

Domain	seller (human)
Virtual	yes
Sensitive	no

Object

Packaging

Domain	packaging
Virtual	no
Sensitive	no

Response

On-site Recommendation

Modality	multimodal (textual and visual)
Complex	yes
Exploits Data	yes
Has Confidence	no

Response

Email Recommendation

Modality	multimodal (textual and visual)
Complex	yes
Exploits Data	yes
Has Confidence	no

Figure 12. Amazon representation according to the UpRISE model: *actors* and *items* (part I: objects and responses).

ITEMS (p. 2)

Widget

Stars (1)

Label	yes (I hate it, I don't like it, It's ok, I like it, I love it)
Visual Metaphor	neutral
Icon	stars
Granularity	5
Range	1-5
Step	1
Point Mutability	no
Positive Negative	no
Neutral Position	yes
Content Type	number
Input Modality	select option

Widget

Stars (2)

Label	yes (terrible, bad, average, good, excellent)
Visual Metaphor	neutral
Icon	stars
Granularity	5
Range	1-5
Step	1
Point Mutability	no
Positive Negative	no
Neutral Position	yes
Content Type	number
Input Modality	select option

Widget

Likert (5-points)

Label	yes (excellent protection, good protection, average protection, mediocre protection, terrible protection)
Visual Metaphor	technical (Likert-like scale)
Icon	*not applicable*
Granularity	5
Range	excellent - terrible protection
Step	*not applicable*
Point Mutability	no
Positive Negative	both
Neutral Position	yes
Content Type	number
Input Modality	select option

Widget

Likert (4-points)

Label	yes (too small, ok, too big, wrong size)
Visual Metaphor	technical (Likert-like scale)
Icon	*not applicable*
Granularity	4
Range	too small - wrong size
Step	*not applicable*
Point Mutability	no
Positive Negative	both
Neutral Position	no
Content Type	number
Input Modality	select option

Figure 13. Amazon representation according to the UpRISE model: *items* (part II: widgets).

ITEMS (p. 3)

Widget

Textarea (title)

Label	*not applicable*
Visual Metaphor	none
Icon	none
Granularity	*not applicable*
Range	*not applicable*
Step	*not applicable*
Point Mutability	*not applicable*
Positive Negative	*not applicable*
Neutral Position	*not applicable*
Content Type	text
Input Modality	text

Widget

Textarea (review)

Label	*not applicable*
Visual Metaphor	none
Icon	none
Granularity	*not applicable*
Range	*not applicable*
Step	*not applicable*
Point Mutability	*not applicable*
Positive Negative	*not applicable*
Neutral Position	*not applicable*
Content Type	text
Input Modality	text

Widget

Radio Buttons

Label	yes (yes, no)
Visual Metaphor	*not applicable*
Icon	none
Granularity	2 or 3
Range	*not applicable*
Step	*not applicable*
Point Mutability	*not applicable*
Positive Negative	both
Neutral Position	no
Content Type	text
Input Modality	select option

Figure 14. Amazon representation according to the UpRISE model: *items* (part III: widgets).

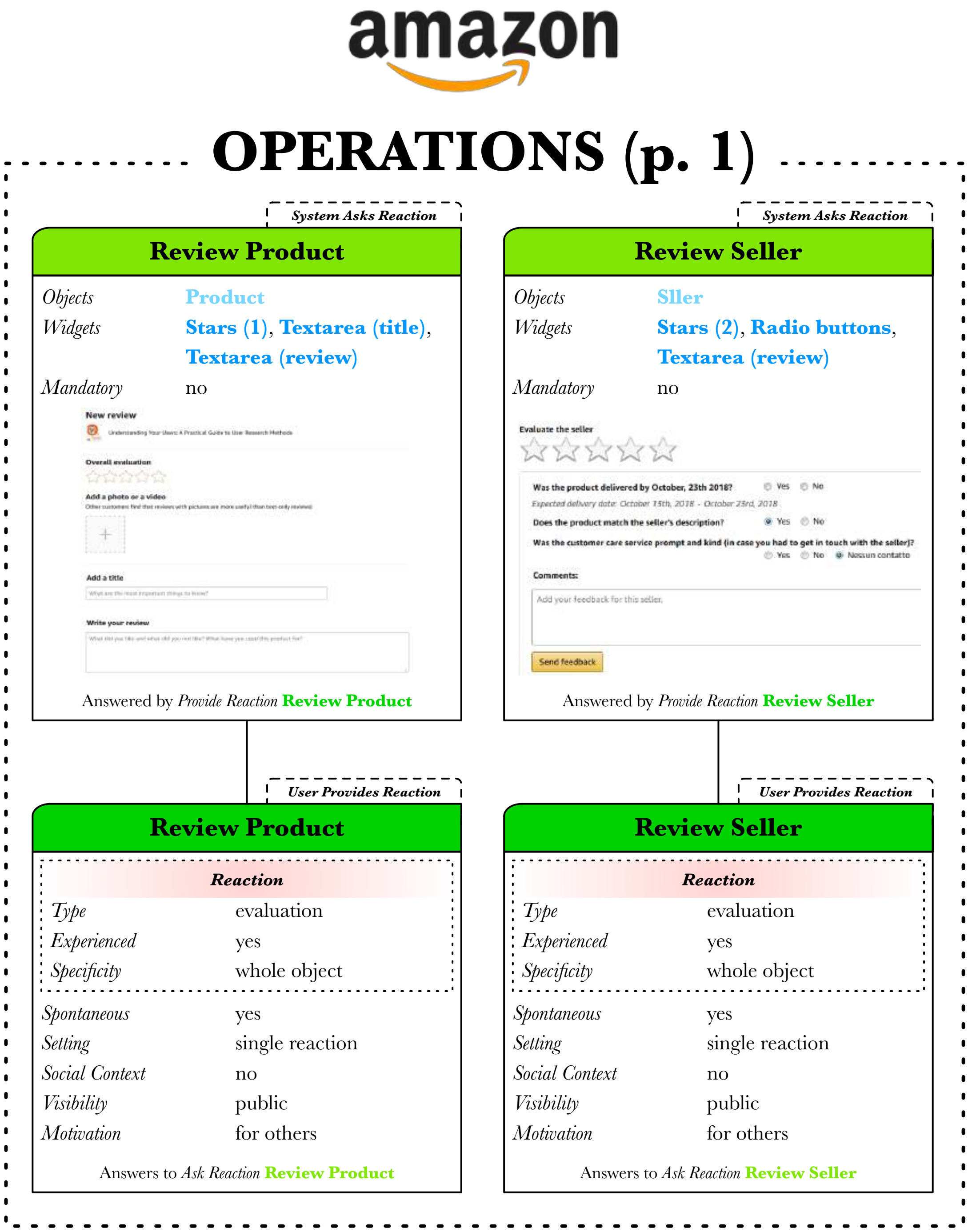


Figure 15. Amazon representation according to the UpRISE model: *operations* (part I: ask reaction and provide reaction).

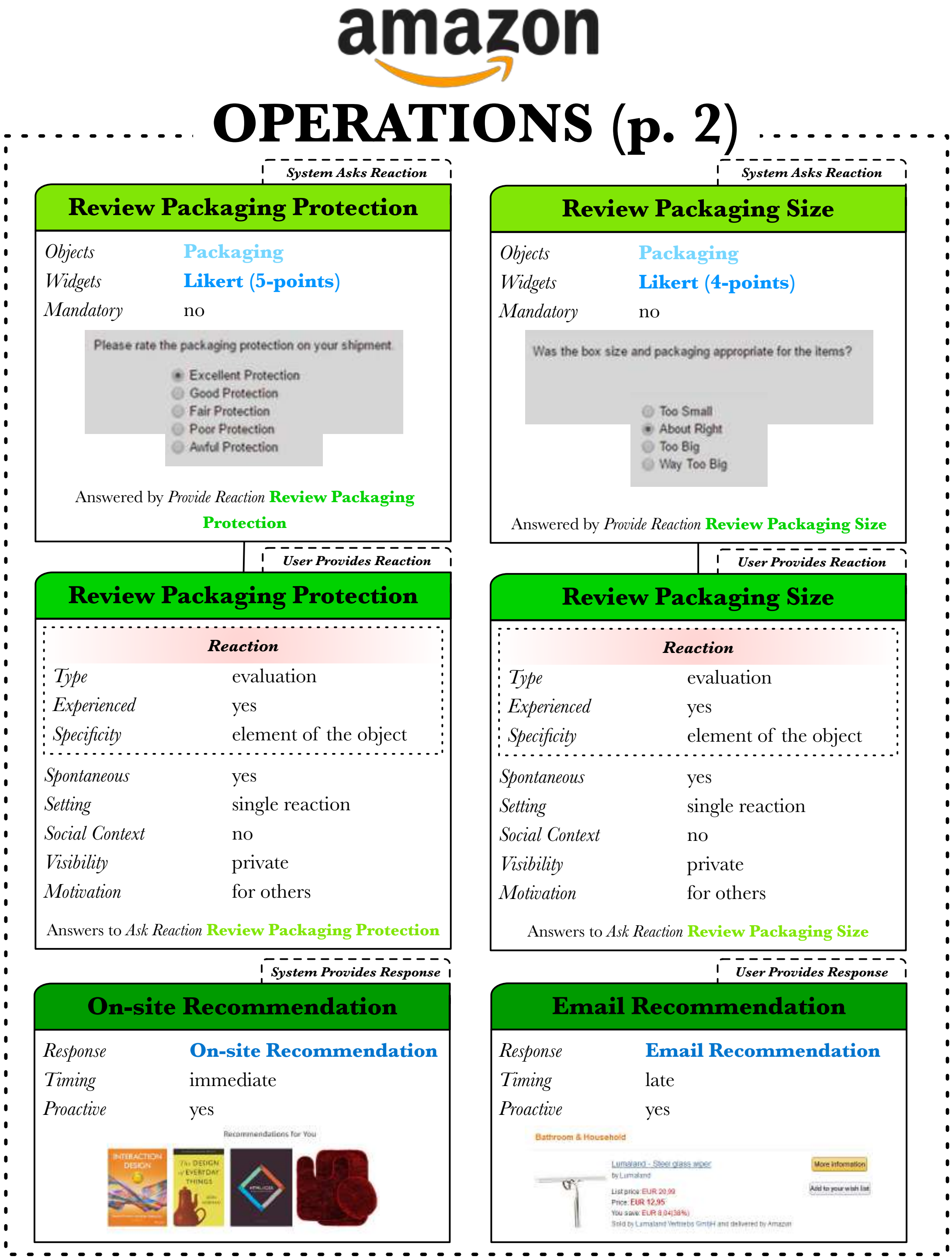


Figure 16. Amazon representation according to the UpRISE model: *operations* (part II: ask reaction, provide reaction and provide response).

6. UpRISE as a comparative tool

According to Beaudouin -LafonBeaudouin-Lafon (2000), HCI models besides being descriptive, prescriptive and generative should also be *comparative*, namely they should provide metrics for comparing alternative designs. Coherently, in this section, we show how our model can be used to compare existing systems, focusing on Amazon, Netflix and Facebook as use cases. In order to ease comparison, we tried to devise intuitive visualizations which can encourage the exploration and intuitive interpretation of data, similarly to Chernoff's faces (Chernoff, 1973). More specifically, we mapped the possible values of all the properties which describe UpRISE elements to different colours and visually represented interactive systems in matrix form Brunetti, Cena, Gena, Mensa, and Vernero (2020), based on the following rules: *i)* matrices correspond to UpRISE elements (e.g. widgets, responses, ...); *ii)* columns correspond to properties; *iii)* rows correspond to element instances; *iv)* sets of rows correspond to systems; *v)* cell colours correspond to values.
For simplicity, in this case we take into account only widgets and the "user provides reaction" operation.

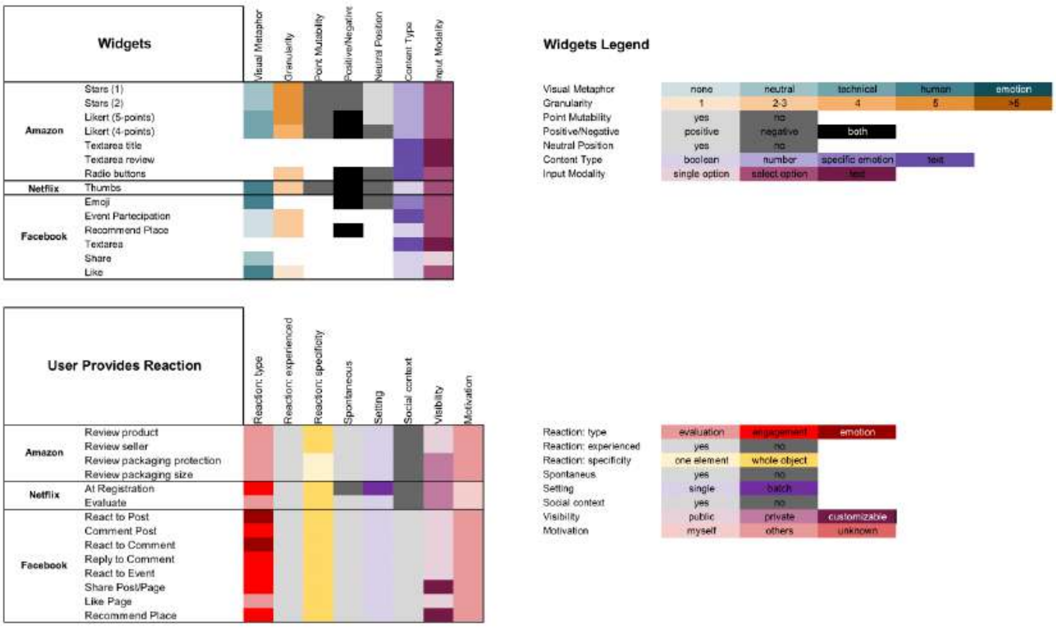


Figure 17. Amazon vs. Netflix vs. Facebook

From Figure 17, it is possible to see at a glance that Facebook and Amazon both use a more extensive range of different widgets than Netflix, and allow users to perform a larger number of "user provides reaction" operations. However, Amazon and Netflix are more similar with respect to the type of reactions they allow, since they both value evaluations, while Facebook almost exclusively concentrates on engagement and emotion. Due to this peculiarity in the reaction type, Facebook also stands out as far as the widget point mutability is concerned: in fact, this property is "not applicable" for all the widgets used in Facebook, showing that widgets used to express emotions and engagement do not normally fall into the category of scales consisting in a series of (similar or different) points. The same considerations can be extended to the "positive/negative" and "neutral position" dimensions, since Facebook mainly uses widgets where these concepts are not applicable. Coherently, regarding granularity, Facebook only uses widgets with either very low granularity, or where this concept is not applicable. On the contrary, aiming at collecting quantitative evaluations, Amazon includes widgets with up to 5 points, while Netflix adopts an "intermediate" approach, using a single widget with low granularity. Similarly, while Amazon uses widgets with a neutral or technical visual metaphor (or for which this concept is not applicable), both Facebook and Netflix have examples on the "human" side. In addition, we can see that in general the three systems are similar with respect to input modality, while the aforementioned differences in their overall goals are also reflected by the "content type" dimension. In fact, Amazon collects numerical and textual reactions, which are especially useful to express precise assessments, while Facebook collects a variety of content types, among which are, notably, specific emotions, and Netflix only collects boolean values.
While the three systems appear less diversified as far as their use of "user provides reaction" operations is concerned, provided that we exclude the number of rows and the "reaction: type" column, it is still interesting to notice that, differently from Amazon and Netflix, in Facebook reactions are always provided in a social context and with public visibility, coherently with the fact that this system focuses on emotion and engagement.

All in all, thanks to our description in terms of the UpRISE model, we can easily conclude that Amazon and Facebook are more complex systems in comparison with Netflix; however, while Amazon aims at collecting precise evaluations, Facebook favours the expression of emotions and engagement. Similarly to Amazon, Netflix also collects evaluations, but, being a simpler system, it favours simpler widgets, which are on the whole more similar to those used by Facebook, to collect users' reactions (Figure 18).

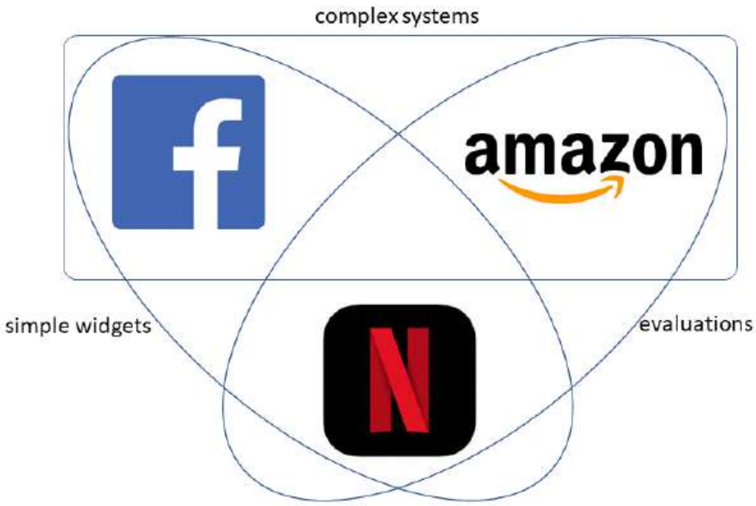


Figure 18. Amazon vs. Netflix vs. Facebook

7. UpRISE as a design reference model

HCI models and theories are often related. While a model tries to simplify the reality, a theory attempts to explain reality (Carroll, 2003). Similarly to models, HCI theories, according to Shneiderman and Bederson (Shneiderman & Bederson, 2003), should be not only *descriptive* (providing concept and terms), *explanatory* (explicating relationship and processes), *predictive* (being able of making predictions), but also *prescriptive* (providing guidance for design), and *generative* (helping to discover or invent something new). Borrowing this theory's classification, we exploit the understanding of the reactions that we have obtained by applying our model to concrete cases to make it **prescriptive**. This means that we aim at using it as a reference model stimulating designers to approach design/redesign tasks in a thorough and well-structured manner, suggesting all the possibly relevant points -some of which designers might otherwise miss- with respect to their goals.

In this section, we present some possible design goals and discuss the questions system designers might ask themselves referring to the UpRISE model, thus exemplifying how it could be used to support design tasks. The six design goals (maximising reaction quantity, maximizing reaction precision, supporting user engagement, increasing user satisfaction, increasing the trust in the system, getting the right data) are adapted from high-level goals coming from the recommender systems literature (Adomavicius, Bockstedt, Curley, & Zhang, 2019; Ekstrand & Willemsen, 2016; Konstan & Riedl, 2012; Nguyen et al., 2013; Ricci et al., 2010; Schnabel, Bennett, & Joachims, 2018; Zou et al., 2019) and from related work on ratings (Cena et al., 2017).

Tables 5,6,7,8,9, 10 present, for each goal, the references to the UpRISE model, the corresponding questions (with rationale) and some design guidelines based on our experience and relevant related work.

Goal 1: Maximizing reaction quantity *i.e., collecting as many reactions as possible*			
UpRISE element	**Questions**	**Question rationale**	**Suggestions**
Items: widget	What *widget* should be provided?	*Depending on their features, widgets might be more or less suitable if users have to provide a large number of reactions. For example, we can hypothesize that pleasant, easy and quick to use widgets might be preferred.*	(1) Prefer simpler widgets (with lower granularity) to promote quantity instead of quality of reactions (lower granularity stimulate extreme ratings, see (Cena et al., 2017)).
Operations: system asks reaction	Should the system make use of *system asks reaction operations* proactively or not?	*The rationale behind this question is that proactively asking users to provide their reactions may stimulate the desired behaviour; however, depending on the timing and frequency of this operation, users might get annoyed and refuse to provide further reactions.*	(1) Make ask reaction mandatory, only if users will have an immediate advantage. (2) If the reactions are linked to mandatory comments, provide suggested comments in order to encourage user reactions. (3) Provide proactive responses to make the system responses to user's reactions understandable.
Operations: system asks reaction	Provided that "system asks reaction" operations are used proactively, should they be *mandatory* or *optional*?	*Binding some functions to the provisioning of a certain number of reactions might have a positive effect. However, as discussed for the previous point, users might as well be bothered by an overly demanding system, and decide to abandon it.*	(1) Use gamification approaches in order to highlight and make visible the possible advantages of proving reactions.

Table 5.: Using the UpRISE model to support possible goals in interactive systems: maximizing reaction quantity

Goal 2: Maximizing reaction precision *i.e., collecting reactions that realistically represent user preferences*			
UpRISE element	**Questions**	**Question rationale**	**Suggestions**
Items: widget	What *widget* should be provided?	*Some widget are more likely to allow users to express precise and truthful preferences. For example, regarding granularity, (Herlocker et al., 2004) pointed out that an appropriate rating scale should allow users to distinguish among exactly as many levels of liking as it makes sense to them. (Weng, 2004) stated that high granularity is more reliable*	(1) Prefer widgets with higher granularity to promote quality of reactions (higher granularity stimulates reasoning, see (Cena et al., 2017)). (2) Provide widgets consistent with the provided reactions (like, love, wow, angry, etc.). (3) Higher granularity stimulate reasoning, lower granularity stimulate extreme ratings (e.g., 10 points granularity encourage higher ratings, more than 2-4-6, see (Cena et al., 2017)). (4) Remember that the kind of widget has an influence on provided reactions (Cena et al., 2017), and numerical proportion in the rating conversions is not always the right choice. Thus, predefined reaction mapping are not enough. (5) More neutral icons, as star, do no affect user reactions. (6) User reactions are domain dependent and socially dependent, so keep the domain and the social context in mind, when analyzing reactions.
Operations: system asks reaction	Should "system asks reaction" operations be *mandatory* or optional?	*Forcing users to express some reaction may have an effect on its quality*	(1) Make ask reaction mandatory, only if users will have an immediate advantage.
Operations: user provides reaction	Should all reactions be *experienced* or not?	*Experienced reactions might be more representative*	(1) Make the system transparent, letting the user know how her reactions are used (Cramer et al., 2008)
Operations: user provides reaction	How *specific* should reactions be, i.e., should they refer to one element or to the whole object?	*Reacting to a whole object vs to some of its parts can be different in terms of cognitive demand and expressiveness, among other things*	(1) Give the possibility to express reactions to some part of the object (e.g. actors for movies)

Table 6.: Using the UpRISE model to support possible goals in interactive systems: maximizing reaction precision

Goal 3: Supporting user engagement with the system *i.e., having users constantly and frequently interact with the systems*			
UpRISE element	**Questions**	**Question rationale**	**Suggestions**
Operations: system asks reaction	Should the system make use of *"system asks reaction" operations* proactively or not?	*Using "system asks reaction" operations proactively might trigger user reactions and favour a constant dialogue between the user and system*	(1) Be careful that users like to immediately have their tasks done (avoid to ask too many steps in asking reactions Carroll and Rosson (1987))
Operations: system provides response	Should the system make use of *"system provides response" operations* or not?	*Using "system provides response" operations might promote user participation, as system responses can be seen as "positive reinforcement" for user reactions*	(1) Always provide a system feedback after reaction. (2) Explain how reactions are used and why.
Operations: system provides response	If *"system provides response" operations* are used, what is the best *timing*, late or immediate?	*Immediate responses might improve the quality of the user/system dialogue, suggesting that the system is highly interactive and able to personalize its behaviour based on user actions. Late responses might serve as a trigger to reignite interaction at times users are not currently engaged with the system.*	(1) Provide non intrusive late responses, in form of personalized suggestions or email suggestions (possibly thanks to user reactions). (2) If you are providing multimedia responses, always remember to provide textual alternatives. (3) Be careful because reactions may be device dependent (e.g. less precise in mobile context).
Operations: system provides response	If *"system provides response" operations* are used, should responses be *proactive*, or should they only follow users' actions?	*Similarly to late responses, proactive responses can draw users' attention to the system. However, proactive responses might fail to catch users' attention, for example if they are not currently interested in the response content or if the system is perceived as too invasive.*	(1) Provide proactive responses to make the system responses to user's reactions understandable.
Operations: system provides response	If *"system provides response" operations* are used, should responses *exploit data* or not?	*Personalized responses based on user-related data might be more likely to raise users' attention (Petty, Cacioppo, & Goldman, 1981).*	(1) If user data are used be always clear in explaining how user data are used and why (be careful to GDPR[8])

Table 7.: Using the UpRISE model to support possible goals in interactive systems: supporting user engagement with the system

[8]https://www.gdpr.net/

Goal 4: Increasing user satisfaction with the system *i.e., having users positively assess their interaction with the system*			
UpRISE element	**Questions**	**Question rationale**	**Suggestions**
Items: widget	What *widget* should be provided?	*Different widgets can be perceived as more pleasant/effective/easy to use. Users might also be allowed to choose the widget they prefer*	(1) If the system possesses a model/profile of the user, different kinds of widgets may be suggested. (2) Give the user the possibility of changing/choosing the preferred widget.
Operations: system provides response	If *"system provides response" operations* are used, what type of response should be provided, as far as *modality* (i.e., textual, visual, audio or multimodal) and *complexity* (i.e., simple or elaborate) are concerned?	*More elaborate responses can be considered more engaging, but users might have different preferences, also due to their context (e.g., device, social setting, etc.)*	(1) If you are providing multimedia responses, always remember to provide textual alternatives.
Operations: system provides response	If *"system provides response" operations* are used, should responses *exploit data* or not?	*Personalized responses can be considered more satisfying (Petty et al., 1981), unless they limit user freedom in an unwanted manner*	(1) Provide personalized responses to raise the user's attention.
Operations: system provides response	If *"system provides response" operations* are used, what is the best *timing*, late or immediate?	*Immediate responses might be more likely to help satisfy users' current needs and might suggest that the system is highly interactive.*	(1) Always provide an immediate feedback to user's reactions.
Operations: system provides response	If *"system provides response" operations* are used, should responses be *proactive*, or should they only follow users' actions?	*Responses that follow users' actions might be more likely to relate to users' needs. Proactive responses might be perceived as invasive, but might also surprise and engage users in a positive way.*	(1)Provide scrutable and transparent systems, offering proofs and explanations of their behavior

Table 8.: Using the UpRISE model to support possible goals in interactive systems: increasing user satisfaction with the system

Goal 5: Increasing user trust in the system *i.e., having users trust the system responses and believe that the system treats the information they provided carefully and ethically*			
UpRISE element	**Questions**	**Question rationale**	**Suggestions**
Actors: system	Should the system provide a low, medium or high level of *transparency* about its use of reactions?	*Information revealing how the system works can support user trust*	(1)Provide short information on system functioning in an easily accessible format. (2) Allow interested users to access detailed information on the use of reactions.
Items: objects	Should the system allow to provide reactions for *sensitive* items or not?	*The way a system deals with potentially delicate social issues (e.g., sensitive items) can affect users' trust in a system.*	(1) In social networks, provide different levels of visibility/privacy for user reactions (all, friends, group of friends, etc).
Items: response	Should the system present a *confidence* assessment for its responses or not?	*Information on confidence might influence users' assessment of system responses, and weaken or strengthen user perceptions of possible errors.*	(1) Providing confidence level of the system may help the user in her decision (see Netflix for example)
Operations: user provides reaction	Should the system make user reactions publicly *visible* or keep them private?	*Systems that keep user reactions private - or that allow users to manage different levels of privacy - might be perceived as more trustworthy.*	(1) Avoid anonymous reactions in order to minimize haters.
Operations: user provides reaction	Provided that reactions are public, should they be associated to their authors?	*Associating reactions to their authors might reinforce the impression that there are "real users" behind the system, and thus increase users' trust.*	(1) Avoid anonymous reactions in order to improve the system credibility.

Table 9.: Using the UpRISE model to support possible goals in interactive systems: increasing user trust in the system

Goal 6: Getting the right data *i.e., collecting reactions which can be used to help users fulfill their needs*			
UpRISE element	**Questions**	**Question rationale**	**Suggestions**
Operations: user provides reaction	Should the system allow users to express reactions for objects they did not experience?	*Collecting reactions about not-yet-experienced objects may provide information about user goals and desires and thus allow for behaviour change support. In fact, users may not be satisfied with their current behaviour and wish to change it (Ekstrand & Willemsen, 2016).*	(1) Allow users to express reactions which mark their interest for and engagement with not-yet-experienced objects.
Operations: user provides reaction	Should the system make user reactions publicly *visible* or keep them private?	*Public and private reactions may reveal different information about a user (e.g., what they think they should like vs. what they like).*	(1) Systems which offer content for private consumption may support private reactions to collect "unbiased" preferences. (2) Reaction visibility (public or private) should be clearly stated.
Operations: user provides reaction	Should the system encourage users to express reactions for their benefit or for the benefit of other users?	*User reactions may depend on their purpose and intended target (e.g., users might positively evaluate a certain object, and yet do not find it suitable for themselves).*	(1) Explain how reactions are used and why.

Table 10.: Using the UpRISE model to support possible goals in interactive systems: getting the right data

8. Conclusions

In this paper, we provide a formal model to describe the dialogue that revolves around user reactions in interactive social systems.

The first purpose of UpRISE is to represent an analytic tool to be used to describe existing systems. We used it for analyzing six of the most popular interactive social systems on the web (Section 5), of different type (e-commerce, media provider, social network) and exploiting different widgets for expressing reactions (emoticons, textboxes, rating scales,...).

The second purpose of UpRISE is to ease the comparison of different systems. We demonstrated how UpRISE can be used to this aim in Section 6, where we also introduced a visual representation based on colour-coded matrices.

The third purpose of the model is to provide a design reference model that stimulates system designers to approach design/redesign tasks in a thorough and well-structured manner, suggesting all the possibly relevant points -some of which designers might otherwise miss- with respect to their goals. In Section 7, we have exemplified how UpRISE model can be used to this purpose.

With regards to our discussion of HCI models in Section 2 UpRISE shows some limitations: we can say that UpRISE is *descriptive*, *prescriptive* and *comparative*, but it is neither *generative* nor *predictive*. In fact, it does not allow to anticipate users' behaviour (or system performances), given a certain set of reaction-related features. Indeed, in Section 7 we showed how different goals, such as maximizing reaction quantity or increasing user satisfaction, can be intuitively associated to reaction-related features. Ideally, with a predictive model, we would be able to make predictions on such aspects starting from a description of system components in terms of our model, being able, for instance, to anticipate which solution may increase the precision of a certain system in terms of collected user reactions, and thus recommendation quality. In order to do so, we should first carefully choose measurable goals, and then collect a large amount of data from real systems to observe patterns and regularities and learn the correlations that may exist between system features and their performances. However, trying to quantify actual system performances might be difficult, due to the fact that we might need to access information that is most likely proprietary, highly valuable and only accessible to system owners.

Embracing a slightly different perspective, as discussed above, the UpRISE model could serve to simulate system behaviour (thanks to its formal representation) and make predictions in a qualitative way, mapping the designer goals to design choices, similarly to what we exemplified in Section 7. Based on this insight, an important area for future work could be to make the UpRISE model generative, and thus useful not just to designers but also to developers, by devising an executable model similar to a model-based user interface on top of it, aimed not just at describing and analyzing reactions but also at generating recommended interface solutions, given one or more goals to maximize as input. Associations similar to those that we described in Section 7, expressed for example in the form of rules as "If widgets with coarse granularity are used, then the number of collected reactions is high", could be used as a basis for such simulations/predictions.

As a formal model, UpRISE helps designers to explore the design space and simulate it, without the need of real implementation, and may lead them to consider new combinations of reaction-related features, or to question their previous choices. By listing a large number of reaction-related aspects, it can also have the additional benefit of stimulating them to reflect on the complexity of reaction management and eventually identify further relevant features. However, UpRISE in itself has the limit of not providing any guidance for the creation of completely new solutions.

The model can be used to automatically create some visualisation for describing and comparing systems, as we did in Section 6. We showed in Section 6 that our model provides a common framework for describing and comparing different systems. However, in UpRISE terms, comparison is limited to be merely qualitative, in that the model does not provide any guidance for system assessment, nor does it offer some concise metric, such as a score or quality level, to summarize system features. In addition, based on our experience, we believe that manually generating formal or visual system descriptions can be daunting. Therefore, in future work we plan to devise intuitive tools to help system analysts and designers to apply and interpret our model. On the one hand, we could design a graphical user interface that allows to describe an interactive system by simply filling in a form with intuitive labels and options (such as those used in the figures in Section 5) and automatically generates the corresponding formal notation. On the other hand, we are now studying how to automatically generate easily digestible visualizations such as those we used in Section 6. As a starting point for this application, we are currently working on the representation of the UpRISE model through XML code. A first draft of the UpRISE XML Schema can be found at `http://www.di.unito.it/~vernerof/uprise/uprise.html`, while an overview tree representation is available in the Appendix of this paper.

In summary, we believe that the strength of the formal model lies in its capability of being used as descriptive, comparative and prescriptive tool. In relation to this last point, thanks to our analysis we have derived guidelines that may help designers to choose the right interface tools and then integrate them in their user interfaces. Partially related to this point, another future work is to test the model with user interface designers, in order to collect their feedback and be able to review our checklist from a user-centered perspective. Moreover, this approach can be seen as the first step towards more transparency in the design of interactive intelligent systems (Sinha & Swearingen, 2002).

References

Abowd, G. D., & Beale, R. (1991). Users systems and interfaces: a unifying framework for interaction. In *D. diaper and n. hammond. proceedings of hci'91: People and computers vi* (p. 73-87). Cambridge: Cambridge University Press.

Adomavicius, G., Bockstedt, J. C., Curley, S. P., & Zhang, J. (2019). Reeducing recommender system biases: An investigation of rating display designs. *MIS Quarterly*, *43*(4).

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge & Data Engineering*(6), 734–749.

Beaudouin-Lafon, M. (2000). Instrumental interaction: An interaction model for designing post-wimp user interfaces. In *Proceedings of the sigchi conference on human factors in computing systems* (pp. 446–453). New York, NY, USA: ACM. Retrieved from `http://doi.acm.org/10.1145/332040.332473`

Brunetti, D., Cena, F., Gena, C., Mensa, E., & Vernero, F. (2020). A color map to compare reactions tools in interactive systems..

Buxton, W. (1990). A three-state model of graphical input. In *Proceedings of the ifip tc13 third interational conference on human-computer interaction* (pp. 449–456). Amsterdam, The Netherlands, The Netherlands: North-Holland Publishing Co. Retrieved from `http://dl.acm.org/citation.cfm?id=647402.725582`

Card, S. K., Moran, T. P., & Newell, A. (1980, July). The keystroke-level model for user performance time with interactive systems. *Commun. ACM*, *23*(7), 396–410. Retrieved from http://doi.acm.org/10.1145/358886.358895

Card, S. K., Moran, T. P., & Newell, A. (1983). *The psychology of human-computer interaction.* Erlbaum. Retrieved from http://www.worldcat.org/oclc/59953542

Carroll, J. M. (Ed.). (2003). *Hci models, theories, and frameworks: Toward a multidisciplinary science.* San Francisco, CA, USA: Morgan Kaufmann Publishers Inc.

Carroll, J. M., & Rosson, M. B. (1987). *Paradox of the active user.*

Cena, F., Gena, C., Grillo, P., Kuflik, T., Vernero, F., & Wecker, A. J. (2017). How scales influence user rating behaviour in recommender systems. *Behaviour & Information Technology*, *36*(10), 985–1004.

Cena, F., & Vernero, F. (2015). A study on user preferential choices about rating scales. *IJTHI*, *11*(1), 33–54. Retrieved from https://doi.org/10.4018/ijthi.2015010103

Cena, F., Vernero, F., & Gena, C. (2010). Towards a customization of rating scales in adaptive systems. In *International conference on user modeling, adaptation, and personalization* (pp. 369–374).

Chernoff, H. (1973). The use of faces to represent points in k-dimensional space graphically. *Journal of the American Statistical Association*, *68*(342), 361-368. Retrieved from https://www.tandfonline.com/doi/abs/10.1080/01621459.1973.10482434

Cheung, C. M. K., & Lee, M. K. O. (2010, April). A theoretical model of intentional social action in online social networks. *Decis. Support Syst.*, *49*(1), 24–30. Retrieved from http://dx.doi.org/10.1016/j.dss.2009.12.006

Cosley, D., Lam, S. K., Albert, I., Konstan, J. A., & Riedl, J. (2003). Is seeing believing?: How recommender system interfaces affect users' opinions. In *Proceedings of the sigchi conference on human factors in computing systems* (pp. 585–592). New York, NY, USA: ACM. Retrieved from http://doi.acm.org/10.1145/642611.642713

Cramer, H. S. M., Evers, V., Ramlal, S., van Someren, M., Rutledge, L., Stash, N., ... Wielinga, B. J. (2008). The effects of transparency on trust in and acceptance of a content-based art recommender. *User Model. User-Adapt. Interact.*, *18*(5), 455–496. Retrieved from https://doi.org/10.1007/s11257-008-9051-3

Dix, A. (2003). Upside-down as and algorithms—computational formalisms and theory. In J. M. Carroll (Ed.), *Hci models, theories, and frameworks: Toward a multidisciplinary science.* San Francisco: Morgan Kaufmann.

Ekstrand, M. D., & Willemsen, M. C. (2016). Behaviorism is not enough: Better recommendations through listening to users. In *Proceedings of the 10th acm conference on recommender systems* (p. 221–224). New York, NY, USA: Association for Computing Machinery. Retrieved from https://doi.org/10.1145/2959100.2959179

Friedman, P. H., H., & Pollack, S. (1993). The biasing effect of scale-checking styles on response to a likert scale. In *Proceedings of the joint statistical meeting* (p. 792–795).

Gutwin, C., Roseman, M., & Greenberg, S. (1996). A usability study of awareness widgets in a shared workspace groupware system. In *Cscw.*

Han, M., & Park, P. (2009). A study of interface design for widgets in web services through usability evaluation. In *Proceedings of the 2nd international conference on interaction sciences: Information technology, culture and human* (pp. 1013–1018). New York, NY, USA: ACM. Retrieved from http://doi.acm.org/10.1145/1655925.1656109

Hartson, H. R., Siochi, A. C., & Hix, D. (1990, July). The uan: A user-oriented representation for direct manipulation interface designs. *ACM Trans. Inf. Syst.*, *8*(3), 181–203. Retrieved from http://doi.acm.org/10.1145/98188.98191

Herlocker, J. L., Konstan, J. A., Terveen, L. G., & Riedl, J. T. (2004, January). Evaluating collaborative filtering recommender systems. *ACM Trans. Inf. Syst.*, *22*(1), 5–53. Retrieved from http://doi.acm.org/10.1145/963770.963772

Hogenboom, A., Bal, D., Frasincar, F., Bal, M., de Jong, F., & Kaymak, U. (2013). Exploiting emoticons in sentiment analysis. In *Proceedings of the 28th annual acm symposium on applied computing* (pp. 703–710).

Ishanka, U. A. P., & Marasinghe, A. (2015, Aug). Supporting user interaction of social network mobile application with multimodal interaction. In *2015 10th asia-pacific symposium on information and telecommunication technologies (apsitt)* (p. 1-3).

Jameson, A., Berendt, B., Gabrielli, S., Cena, F., Gena, C., Vernero, F., & Reinecke, K. (2014). Choice architecture for human-computer interaction. *Foundations and Trends in Human-Computer Interaction*, *7*(1-2), 1–235. Retrieved from `https://doi.org/10.1561/1100000028`

Kieras, D. (1994). *A guide to goms task analysis.*

Kluver, D., Nguyen, T. T., Ekstrand, M., Sen, S., & Riedl, J. (2012). How many bits per rating? In *Proceedings of the sixth acm conference on recommender systems* (pp. 99–106).

Konstan, J. A., & Riedl, J. (2012). Recommender systems: from algorithms to user experience. *User Model. User-Adapt. Interact.*, *22*(1-2), 101–123. Retrieved from `https://doi.org/10.1007/s11257-011-9112-x`

Lim, H.-E. (2008, Jun 01). The use of different happiness rating scales: Bias and comparison problem? *Social Indicators Research*, *87*(2), 259–267. Retrieved from `https://doi.org/10.1007/s11205-007-9171-x`

MacKenzie, I. S. (2003). Motor behaviour models for human-computer interaction. In J. M. Carroll (Ed.), *Hci models, theories, and frameworks: Toward a multidisciplinary science* (p. 27-54). San Francisco: Morgan Kaufmann.

Meixner, G., Paternò, F., & Vanderdonckt, J. (2011). Past, present, and future of model-based user interface development. *i-com*, *10*(3), 2–11. Retrieved from `https://doi.org/10.1524/icom.2011.0026`

Nguyen, T., Kluver, D., Wang, T.-Y., Hui, P.-M., Ekstrand, M., Willemsen, M., & Riedl, J. (2013, 10). Rating support interfaces to improve user experience and recommender accuracy. In (p. 149,156).

Nielsen, J. (1993, 11). Iterative user-interface design. *Computer*, *26*, 32-41. Retrieved from `doi.ieeecomputersociety.org/10.1109/2.241424`

Norman, D. A. (1988). *The design of everyday things.* New York: Doubleday Press.

Norman, D. A. (2002). *The design of everyday things.* New York, NY, USA: Basic Books, Inc.

Paramythis, A., Weibelzahl, S., & Masthoff, J. (2010, Dec 01). Layered evaluation of interactive adaptive systems: framework and formative methods. *User Modeling and User-Adapted Interaction*, *20*(5), 383–453. Retrieved from `https://doi.org/10.1007/s11257-010-9082-4`

Petty, R., Cacioppo, J., & Goldman, R. (1981). Personal involvement as a determinant of argument-based persuasion. *Journal of Personality and Social Psychology*, *41(5)*, 847–855.

Preston, C. C., & Colman, A. M. (2000). Optimal number of response categories in rating scales: reliability, validity, discriminating power, and respondent preferences. *Acta psychologica*, *104*(1), 1–15.

Rastogi, P., & Singh, V. (2016). Systematic evaluation of social recommendation systems: Challenges and future dimensions. *International Journal of Advanced Computer Science and Applications*, *7*(4).

Rezabek, L., & Cochenour, J. (1998). Visual cues in computer-mediated communication: Supplementing text with emoticons. *Journal of Visual Literacy*, *18*(2), 201–215.

Ricci, F., Rokach, L., Shapira, B., & Kantor, P. B. (2010). *Recommender systems handbook* (1st ed.). Berlin, Heidelberg: Springer-Verlag.

Rogers, Y. (2012). *Hci theory: Classical, modern, and contemporary* (1st ed.). Morgan & Claypool Publishers.

Rojas, S. L., Kirschenmann, U., & Wolpers, M. (2012). We have no feelings, we have emoticons;-. In *Advanced learning technologies (icalt), 2012 ieee 12th international conference on* (pp. 642–646).

Ruan, L. (2011). Meaningful signs—emoticons. *Theory and Practice in Language Studies*, *1*(1), 91–94.

Schnabel, T., Bennett, P., & Joachims, T. (2018, 02). Improving recommender systems beyond the algorithm.

Shaftel, J., Nash, B. L., & Gillmor, S. (2012). Effects of the number of response categories on rating scales. In *Proceedings of the annual conference of the american educational research association* (pp. 1–24).

Shneiderman, B., & Bederson, B. B. (2003). *The craft of information visualization: Readings and reflections.* San Francisco, CA, USA: Morgan Kaufmann Publishers Inc.

Sinha, R., & Swearingen, K. (2002). The role of transparency in recommender systems. In *Chi'02 extended abstracts on human factors in computing systems* (pp. 830–831).

Sparling, E. I., & Sen, S. (2011). Rating: How difficult is it? In *Proceedings of the fifth acm conference on recommender systems* (pp. 149–156). New York, NY, USA: ACM. Retrieved from `http://doi.acm.org/10.1145/2043932.2043961`

Swearingen, K., & Sinha, R. (2002). Interaction design for recommender systems. In *Privacy, security, risk and trust (passat) and 2011 ieee third inernational conference on social computing (socialcom), 2011 ieee third international conference on.* ACM.

Usman, Z.-u.-h., Alghamdi, F. A., Tariq, A., & Puri, T. N. (2010). Relative ranking – a biased rating. In T. Sobh (Ed.), *Innovations and advances in computer sciences and engineering* (pp. 25–29). Dordrecht: Springer Netherlands.

Van Barneveld, J., & Van Setten, M. (2004). Designing usable interfaces for tv recommender systems. In *Personalized digital television: Targeting programs to individual viewers* (pp. 259–285). Dordrecht: Springer Netherlands. Retrieved from `https://doi.org/10.1007/1-4020-2164-X_10`

Vaz, P. C., Ribeiro, R., & De Matos, D. M. (2013). Understanding the temporal dynamics of recommendations across different rating scales. In *Umap workshops.*

Weijters, E. C., B., & Schillewaert, N. (2001). Do numeric values influence subjects responses to rating scales? *Journal of International Marketing and Marketing Research*, *26*, 41-46.

Weijters, E. C., B., & Schillewaert, N. (2010). The effect of rating scale format on response styles: The number of response categories and response category labels. *International Journal of Research in Marketing*, *27*(3), 236–247.

Weng, L.-J. (2004). Impact of the number of response categories and anchor labels on coefficient alpha and test-retest reliability. *Educational and Psychological Measurement*, *64*(6), 956-972.

Yuasa, M., Saito, K., & Mukawa, N. (2006). Emoticons convey emotions without cognition of faces: an fmri study. In *Chi'06 extended abstracts on human factors in computing systems* (pp. 1565–1570).

Zou, L., Xia, L., Ding, Z., Song, J., Liu, W., & Yin, D. (2019, 07). Reinforcement learning to optimize long-term user engagement in recommender systems. In (p. 2810-2818).

Appendix A. Appendix

A.1. System descriptions according to UpRISE model

A.1.1. Youtube

YouTube is a video-sharing website. It allows registered users to upload, view, rate, share, add to favorites, report, comment on videos, and subscribe to other users, while unregistered users can only watch videos.

In terms of the UpRISE framework, all the video contents managed by YouTube correspond to a single object, i.e., the "Video' (Figure A1, "Video" box). Notice that videos can be considered as sensitive if they contain personal material and viewers know the authors.

Reactions to videos can be provided at any time and the system does not offer any explicit explanation regarding their use. Thus, we believe that the system has a low level of transparency (Figure A1, "YouTube" box).

YouTube makes use of a "thumbs-up/thumbs down" widget, which allows users to express their liking or disliking for videos (Figure A1, "Thumbs" box). In the past, instead, it used a 5-point star rating scale. In addition, it offers the possibility to express reactions in the form of free-text comments (Figure A1, "Textarea" box).

Youtube offers only one type of response, i.e., some type of recommendation (Figure A1, "Recommendation" box). More specifically, recommendations, i.e., videos that can probably be considered similar to those liked and watched by the users (e.g., belonging to the same category), are listed in their homepage. Moreover, YouTube website can be explicitly customized: in fact, users can choose what they want to see in their homepage based on the videos they liked and on the channels they subscribed to.

Users are free to provide reactions to videos at any time, and there are no explicit requests to provide reactions. Thus, YouTube makes use of only two generic "system asks reaction" operations (Figure A2, "System Asks Reaction: Evaluate" and "System Asks Reaction: Comment" boxes).

Similarly, there are two types of "user provides reaction" operations (Figure A2, "User Provides Reaction: Evaluate" and "User Provides Reaction: Comment" boxes).

Finally, YouTube makes use of a single "system provides response" operation to suggest recommendations (Figure A2, "System Provides Response: Recommendation" box). Probably, metadata about videos are used to compute similarity, and recommendations of similar videos are generated taking into account the videos users watched and liked.

ACTORS

System

Youtube

Rating Transparency	low
Objects	[**Video**]
Widgets	[**Thumbs**, **Textarea**]
Responses	[**Recommendation**]

ITEMS

Object

Video

Domain	user generated videos, movies, trailers, music videos, tv series, documentaries, etc
Virtual	yes
Sensitive	possibly yes

Widget

Thumbs

Label	no
Visual Metaphor	human
Icon	thumb up, thumb down
Granularity	2
Range	*not applicable*
Step	*not applicable*
Point Mutability	no
Positive Negative	both
Neutral Position	no
Content Type	boolean
Input Modality	select option

Widget

Textarea

Label	*not applicable*
Visual Metaphor	none
Icon	none
Granularity	*not applicable*
Range	*not applicable*
Step	*not applicable*
Point Mutability	*not applicable*
Positive Negative	*not applicable*
Neutral Position	*not applicable*
Content Type	text
Input Modality	text

Response

Recommendation

Modality	multimodal (textual/visual)
Complexity	elaborate
Exploits Data	yes
Has Confidence	no

Figure A1. YouTube representation according to the UpRISE model: *actors* and *items*.

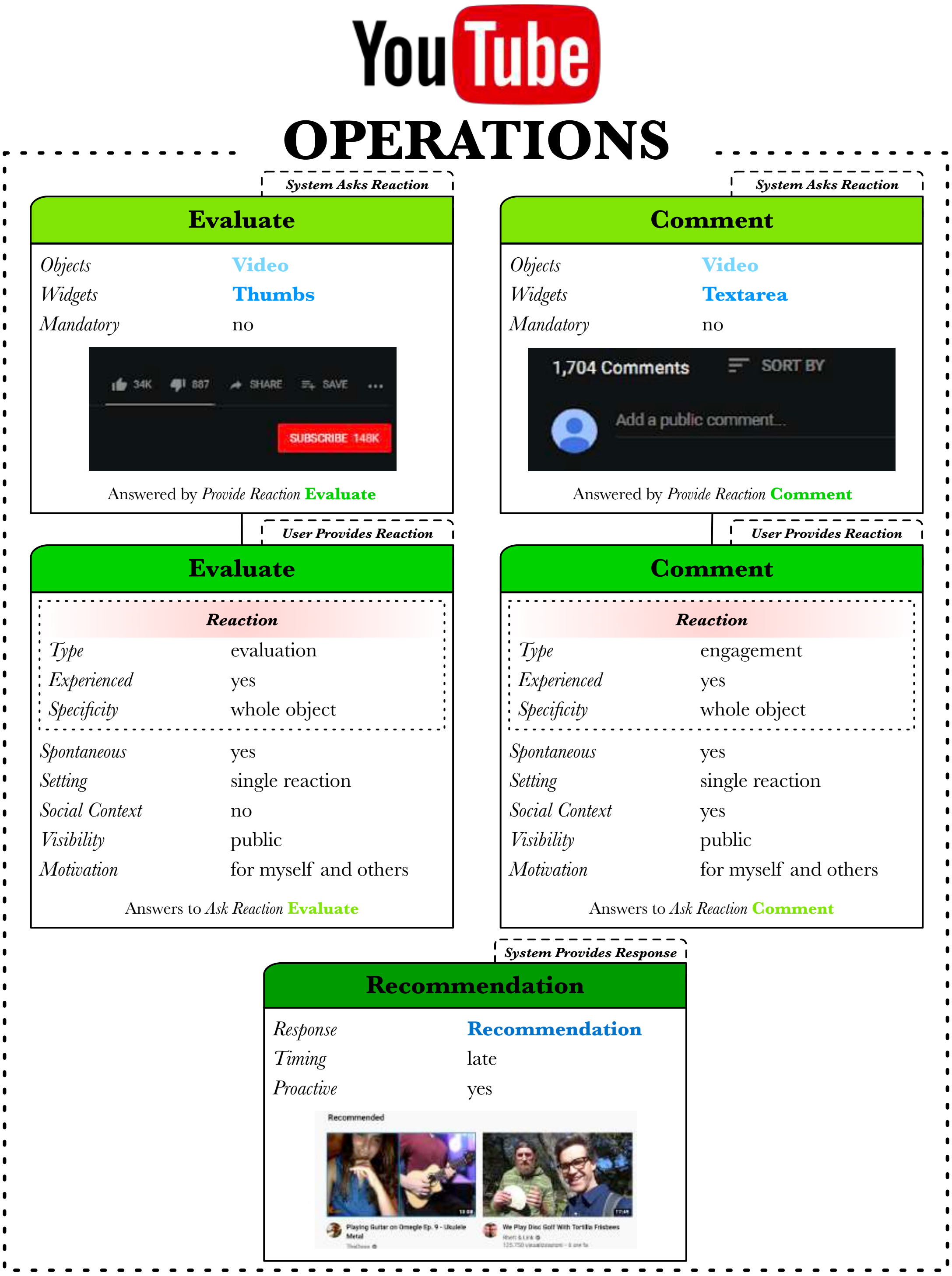


Figure A2. YouTube representation according to the UpRISE model: *operations*.

A.1.2. Instagram

Instagram is a mobile, desktop, and Internet-based photo-sharing application and service that allows users to share pictures and videos either publicly, or privately to pre-approved followers.

Instagram manages a single type of object, i.e., photos (Figure A3, “Photo” box).

In Instagram, reactions can be expressed at any time and the system does not provide any explanation about how they will be used by the system: thus, we assess the system transparency as “low” (Figure A3, “Instagram” box).

Reactions can be expressed through a simple heart-shaped, one-point widget which only allows users to “approve” the photos they like (Figure A3, “Heart” box). In addition, Instagram allows users to express reactions in the form of free-text comments (Figure A3, “Textarea” box).

As far as responses are concerned, Instagram offers recommendations suggesting either people to follow or specific posts to explore (Figure A3, “Recommendation” box).

In Instagram, there are no explicit requests to provide reactions: instead, users can provide them at any time. Thus, Instagram makes use only of two generic “system asks reaction” operations (Figure A4, “System Asks Reaction: Like” and “System Asks Reaction: Comment” boxes).

Coherently, Instagram allows two types of “user provides reaction” operations (Figure A4, “User Provides Reaction: Like” and “User Provides Reaction: Comment” boxes).

Instagram provides recommendations as a response to users (Figure A4, “System Provides Response: Recommendation” box). However, it is not clear how user reactions are used to compute recommendations. We surmise that metadata about pictures are used to compute similarity.

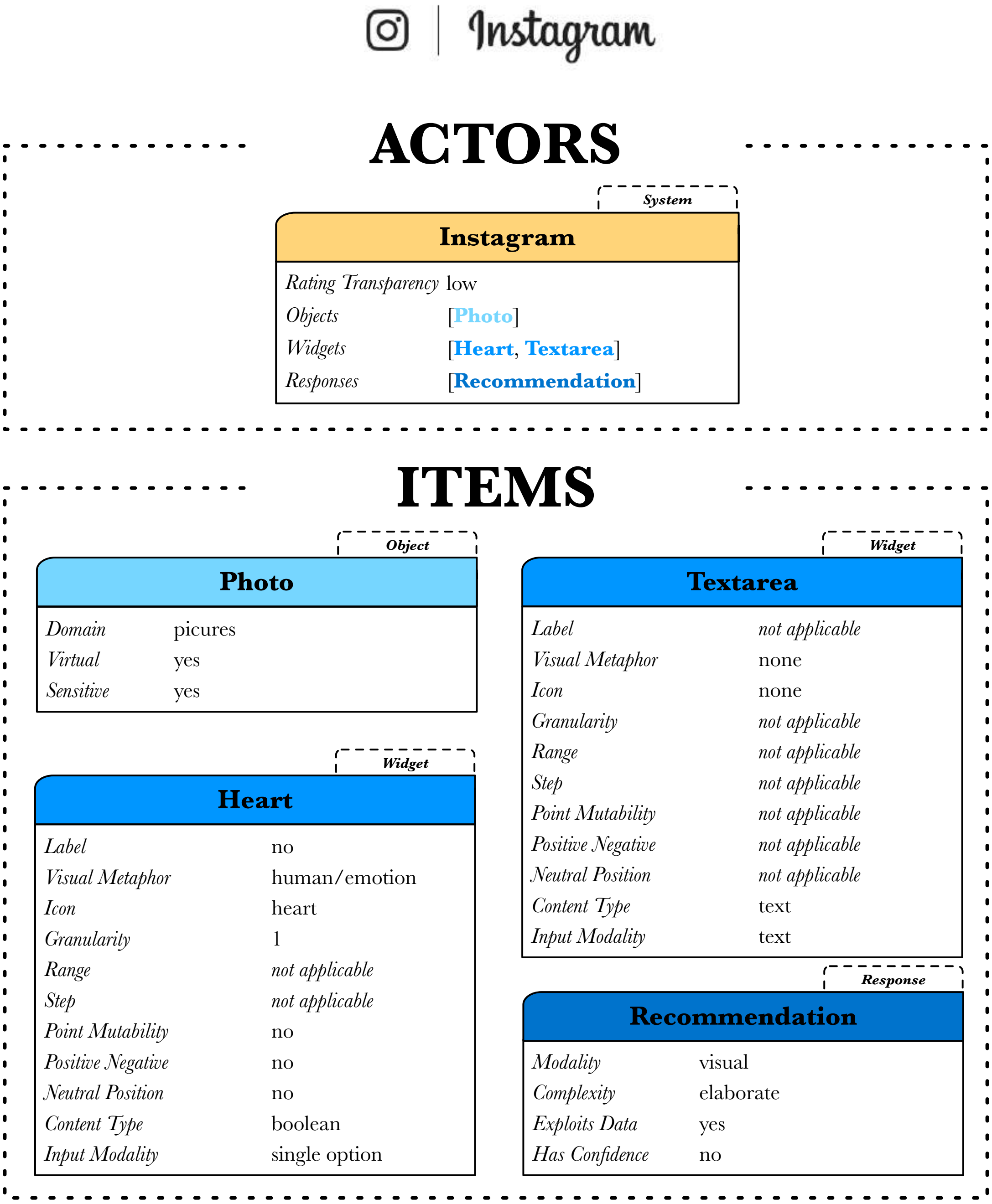


Figure A3. Instagram representation according to the UpRISE model: *actors* and *items*.

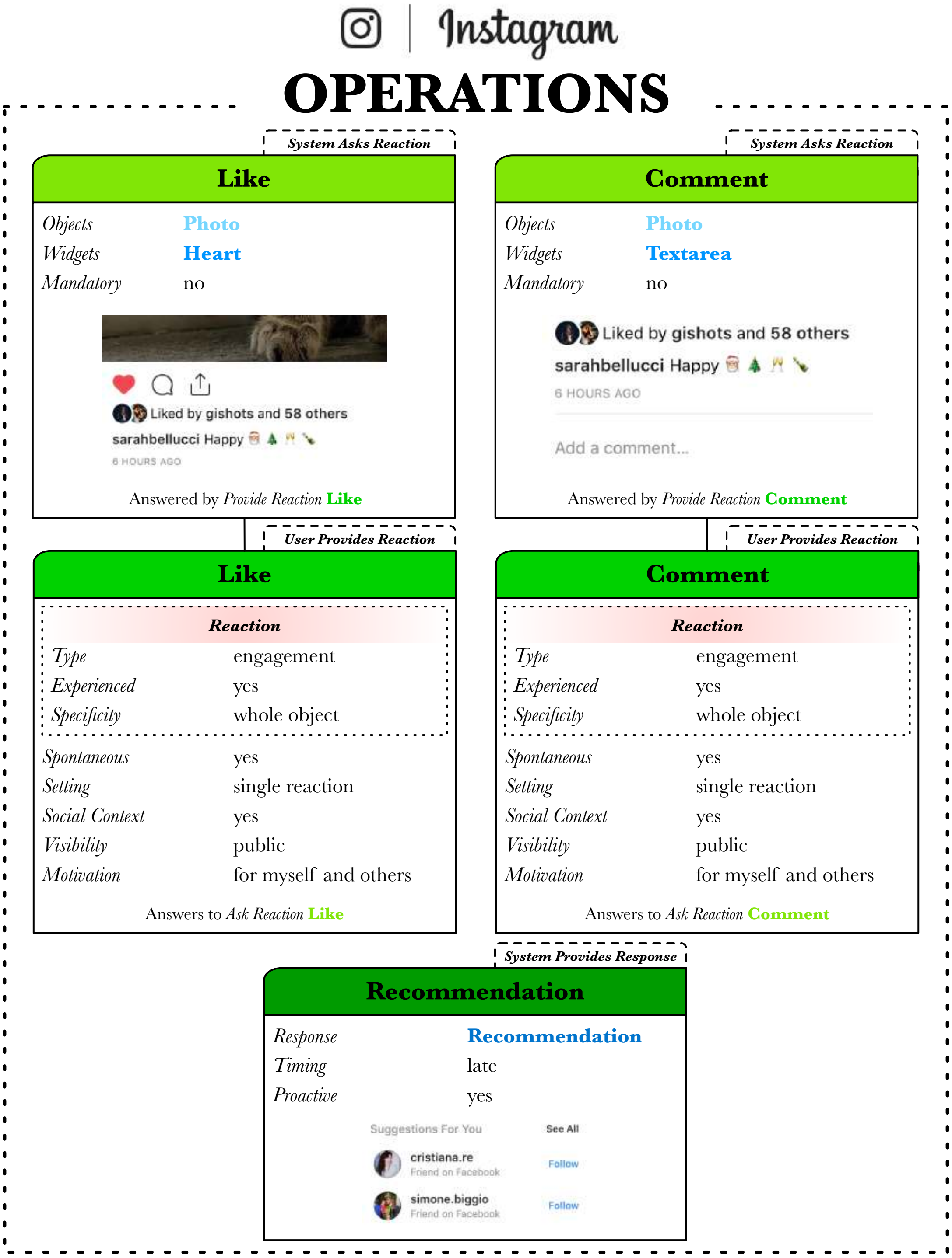


Figure A4. Instagram representation according to the UpRISE model: *operations*.

A.1.3. Twitter

Twitter is an online microblogging service where users post short messages called “tweets”.

Twitter manages a single type of object, the aforementioned “tweet”, i.e., a short multimedia post about virtually any topic (Figure A5, “Tweet” box).

When users provide reactions for tweets, Twitter does not explain how they are used. Recommendations (which can refer to both “tweets” and user accounts to follow) seem to be based mainly on the behaviour of other users (in a “users you follow also follow...” style), rather than on one’s own reactions. Therefore, we consider Twitter level of transparency on its use of reactions as “low” (Figure A5, “Twitter” box).

Reactions can be expressed through a simple heart-shaped, one-point widget which only allows users to “approve” the “tweets” they like (Figure A5, “Heart” box). In addition, Twitter offers the possibility to express reactions in the form of free-text comments (Figure A5, “Textarea” box), as well as to share Tweets with other users (Figure A6, “Share” box).

Twitter offers a single type of response, i.e., recommendations on tweets to read and new accounts to follow (Figure A5, “Recommendation” box).

In Twitter, user can freely provide reactions while they are browsing “tweets”. Thus, there are three generic “system asks reaction” operations (Figure A6, “System Asks Reaction: Share Tweet” and Figure A7, “System Asks Reaction: Like” and “System Asks Reaction: Comment” boxes), and three types of “user provides reaction” operations (Figure A6, “User Provides Reaction: Share Tweet” and Figure A7, “User Provides Reaction: Like” and “User Provides Reaction: Comment” boxes). Similarly to Amazon, in Twitter there are two types of “system provides response’ operations, both corresponding to the “recommendation” response type. In fact, recommendations can be delivered either on Twitter website, in the “Who to follow” section (Figure A7, “System Provides Response: Website Recommendation” box), or via email (Figure A7, “System Provides Response: Email Recommendation” box). Website recommendations are refreshed each time users reload the page and following users’ explicit requests for new recommendations.

ACTORS

System

Twitter

Rating Transparency	low
Objects	[**Tweet**]
Widgets	[**Heart**, **Textarea**, **Share**]
Responses	[**Recommendation**]

ITEMS (p. 1)

Object

Tweet

Domain	tweet (short multimedia post)
Virtual	yes
Sensitive	yes

Widget

Heart

Label	no
Visual Metaphor	human/emotion
Icon	heart
Granularity	1
Range	*not applicable*
Step	*not applicable*
Point Mutability	no
Positive Negative	no
Neutral Position	no
Content Type	boolean
Input Modality	single option

Widget

Textarea

Label	*not applicable*
Visual Metaphor	none
Icon	none
Granularity	*not applicable*
Range	*not applicable*
Step	*not applicable*
Point Mutability	*not applicable*
Positive Negative	*not applicable*
Neutral Position	*not applicable*
Content Type	text
Input Modality	text

Response

Recommendation

Modality	multimodal (textual/visual)
Complex	yes
Exploits Data	yes
Has Confidence	no

Figure A5. Twitter representation according to the UpRISE model: *actors* and *items (1)*.

ITEMS (p. 2)

Widget

Share

Label	none
Visual Metaphor	neutral
Icon	arrow
Granularity	*not applicable*
Range	*not applicable*
Step	*not applicable*
Point Mutability	*not applicable*
Positive Negative	*not applicable*
Neutral Position	*not applicable*
Content Type	boolean
Input Modality	single option

OPERATIONS (p. 1)

System Asks Reaction

Share Tweet

Objects	**Tweet**
Widgets	**Share**
Mandatory	no

Answered by *Provide Reaction* **Share Tweet**

User Provides Reaction

Share Tweet

Reaction

Type	engagement
Experienced	yes
Specificity	whole object

Spontaneous	yes
Setting	single reaction
Social Context	yes
Visibility	customizable
Motivation	for myself and others

Answers to *Ask Reaction* **Share Tweet**

Figure A6. Twitter representation according to the UpRISE model: *items (2)* and *operations (1)*.

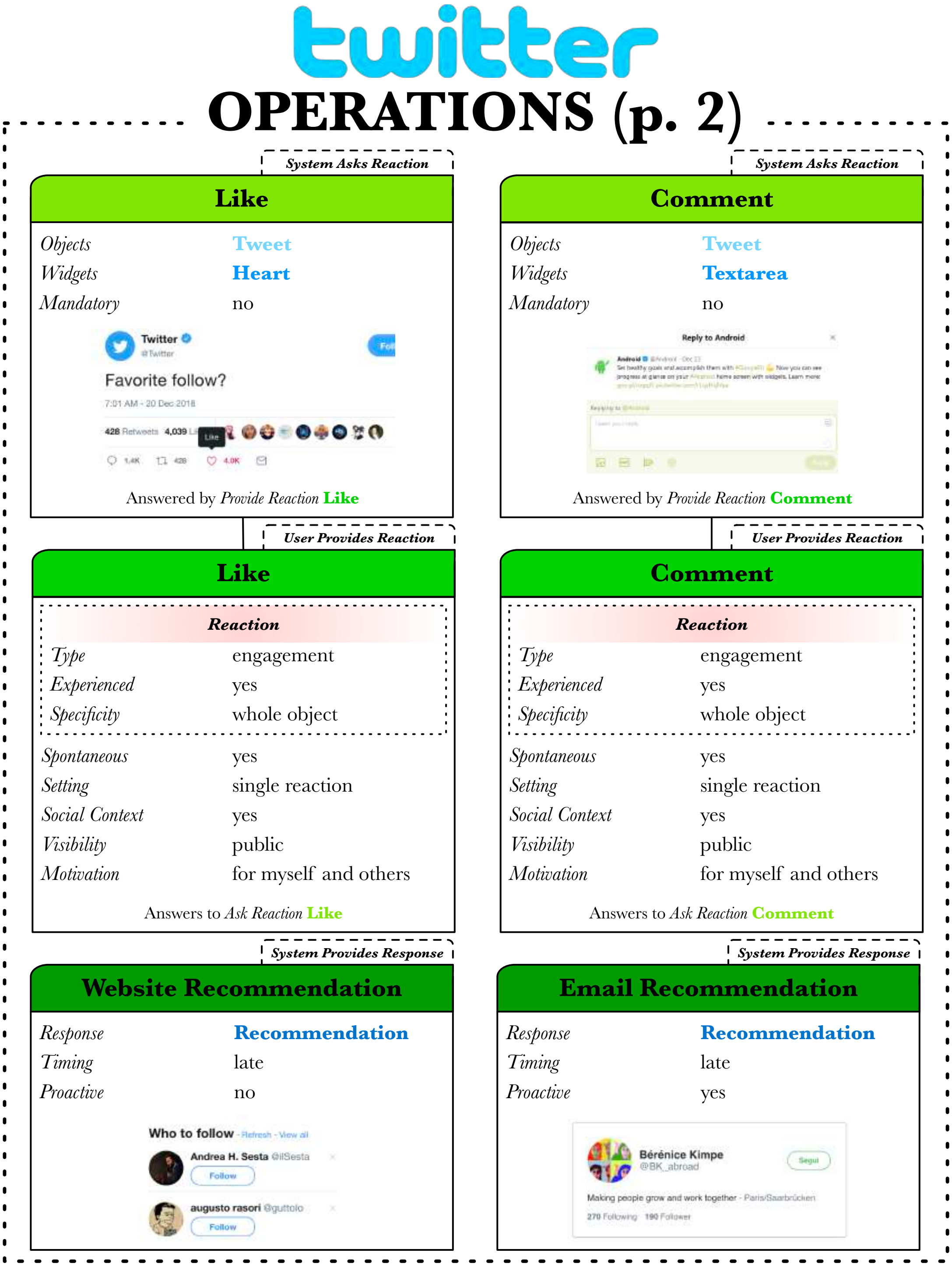


Figure A7. Twitter representation according to the UpRISE model: *operations (2)*.

A.1.4. Facebook

Facebook is an American for-profit corporation and an online social networking service, launched in 2004 by Mark Zuckerberg. Counting 2.2 billion users, Facebook represents the most popular social network at present.

Facebook users can express their reactions for four kinds of objects: posts, official pages showcasing products, brands, places and all sort of items other than events, events and comments (Figure A8, “Post”, “Page”, “Event” and “Comment” boxes).

Facebook does not provide information on its use of reactions; however, posts in the users' homepage appear to be selected and ranked based on their behaviour and reactions. Therefore, we consider Facebook level of transparency on its use of reactions as “low” (Figure A8, “Facebook” box).
Reactions can be expressed through six different widgets: a simple “thumbs up” widget, which only allows users to “approve” the pages they like (Figure A10, “Like” box); an “emoji” widget, used to react to posts (Figure A9, “Emoji” box); an “enhanced” textarea used to express reactions in the form of free-text and multimedia comments (Figure A9, “Textarea” box); an “event participation” widget, used to react to events (Figure A9, “Event participation” box), a “Recommend Place” widget, used to suggest official pages to other users (Figure A9, “Recommend Place” box) and a “Share” widget, used to share posts with other users (Figure A10, “Share” box).

Facebook recommends any type of content: posts, people, events, groups, official pages, sponsored content and so on. All these recommendations are treated in a similar way; hence we take into account a single type of response, i.e., the recommendation (Figure A8, “Recommendation” box).

In Facebook, user can freely provide reactions while they are browsing contents. The system makes use of eight different “system asks reaction” operations. In fact, Facebook asks users to react to posts by expressing an emotion (Figure A10, “React to Post” box), by sharing the post (or page) itself (Figure A13, “Share Post/Page” box), or by replying with a comment (Figure A11, “Comment Post” box). As for comments, the system asks users to either express an emotion or reply with another comment (Figure A11, “React to Comment” box, and Figure A12 “Reply to Comment” box). Finally, users are asked to like pages (Figure A13, “Like Page” box), recommend places, i.e., special pages that present places such as geographical areas, shops and other points of interest (Figure A14, “Recommend Place” box) and react to events (Figure A12, “React to Event” box).

Users answer Facebook requests through the corresponding “user provides reaction” operations (Figure A10, “React to Post” box, Figure A11, “Comment Post” and “React to Comment” boxes, Figure A12, “Reply to Comment” and “React to Event” boxes, Figure A13, “Share Post/Page” and “Like Page” boxes, and Figure A14, “Recommend Place” box).

Finally, Facebook provides recommendations to users through the “system provides response” operation, corresponding to the “recommendation” response type (Figure A14, “System Provides Response: Recommendation” box).

ACTORS

System

Facebook

Rating Transparency	low
Objects	[**Post**, **Page**, **Event**, **Comment**]
Widgets	[**Like**, **Emoji**, **Textarea**, **Recommend**, **Share**, **Event Reaction**]
Responses	[**Recommendation**]

ITEMS (p. 1)

Object

Post

Domain	multimedia post (images, text, gifs, videos, etc)
Virtual	yes
Sensitive	yes

Object

Event

Domain	official page of event, with videos, images and text.
Virtual	yes
Sensitive	yes

Object

Page

Domain	profile page, relating to various topics except events, for example places, books, movies, etc.
Virtual	yes
Sensitive	yes

Object

Comment

Domain	multimedia element that is attached to a post, page or event (images, text, gifs, videos, etc)
Virtual	yes
Sensitive	yes

Response

Recommendation

Modality	multimodal (textual/visual)
Complexity	elaborate
Exploits Data	yes
Has Confidence	no

Figure A8. Facebook representation according to the UpRISE model: *actors* and *items (1)*.

facebook

ITEMS (p. 2)

Widget

Emoji

Label	yes (like, love, ahah, wow, sad, angry)
Visual Metaphor	human
Icon	thumb up, heart, squinchy-eyed grin, surprised face, crying face, angry face
Granularity	*not applicable*
Range	*not applicable*
Step	*not applicable*
Point Mutability	*not applicable*
Positive Negative	both
Neutral Position	no
Content Type	specific emotion
Input Modality	select option

Widget

Recommend Place

Label	yes, no
Visual Metaphor	none
Icon	button
Granularity	2
Range	*not applicable*
Step	*not applicable*
Point Mutability	*not applicable*
Positive Negative	yes
Neutral Position	no
Content Type	boolean
Input Modality	select option

Widget

Event Partecipation

Label	interested, not interested, going
Visual Metaphor	none
Icon	button
Granularity	3
Range	*not applicable*
Step	*not applicable*
Point Mutability	*not applicable*
Positive Negative	*not applicable*
Neutral Position	*not applicable*
Content Type	text
Input Modality	select option

Widget

Textarea

Label	*not applicable*
Visual Metaphor	none
Icon	none
Granularity	*not applicable*
Range	*not applicable*
Step	*not applicable*
Point Mutability	*not applicable*
Positive Negative	*not applicable*
Neutral Position	*not applicable*
Content Type	multimedia
Input Modality	text

Figure A9. Facebook representation according to the UpRISE model: *items (2)*.

facebook

ITEMS (p. 3)

Widget

Share	
Label	no
Visual Metaphor	none
Icon	arrow
Granularity	*not applicable*
Range	*not applicable*
Step	*not applicable*
Point Mutability	*not applicable*
Positive Negative	*not applicable*
Neutral Position	*not applicable*
Content Type	boolean
Input Modality	single option

Widget

Like	
Label	like
Visual Metaphor	human
Icon	thumb up
Granularity	1
Range	*not applicable*
Step	*not applicable*
Point Mutability	*not applicable*
Positive Negative	*not applicable*
Neutral Position	*not applicable*
Content Type	boolean
Input Modality	select option

OPERATIONS (p. 1)

System Asks Reaction

React to Post	
Objects	**Post**
Widgets	**Emoji**
Mandatory	no

Answered by *Provide Reaction* **React to Post**

User Provides Reaction

React to Post	
Reaction	
Type	emotion
Experienced	yes
Specificity	whole object
Spontaneous	yes
Setting	single reaction
Social Context	yes
Visibility	public
Motivation	for myself and others

Answers to *Ask Reaction* **React to Post**

Figure A10. Facebook representation according to the UpRISE model: *items (3)* and *operations (1)*.

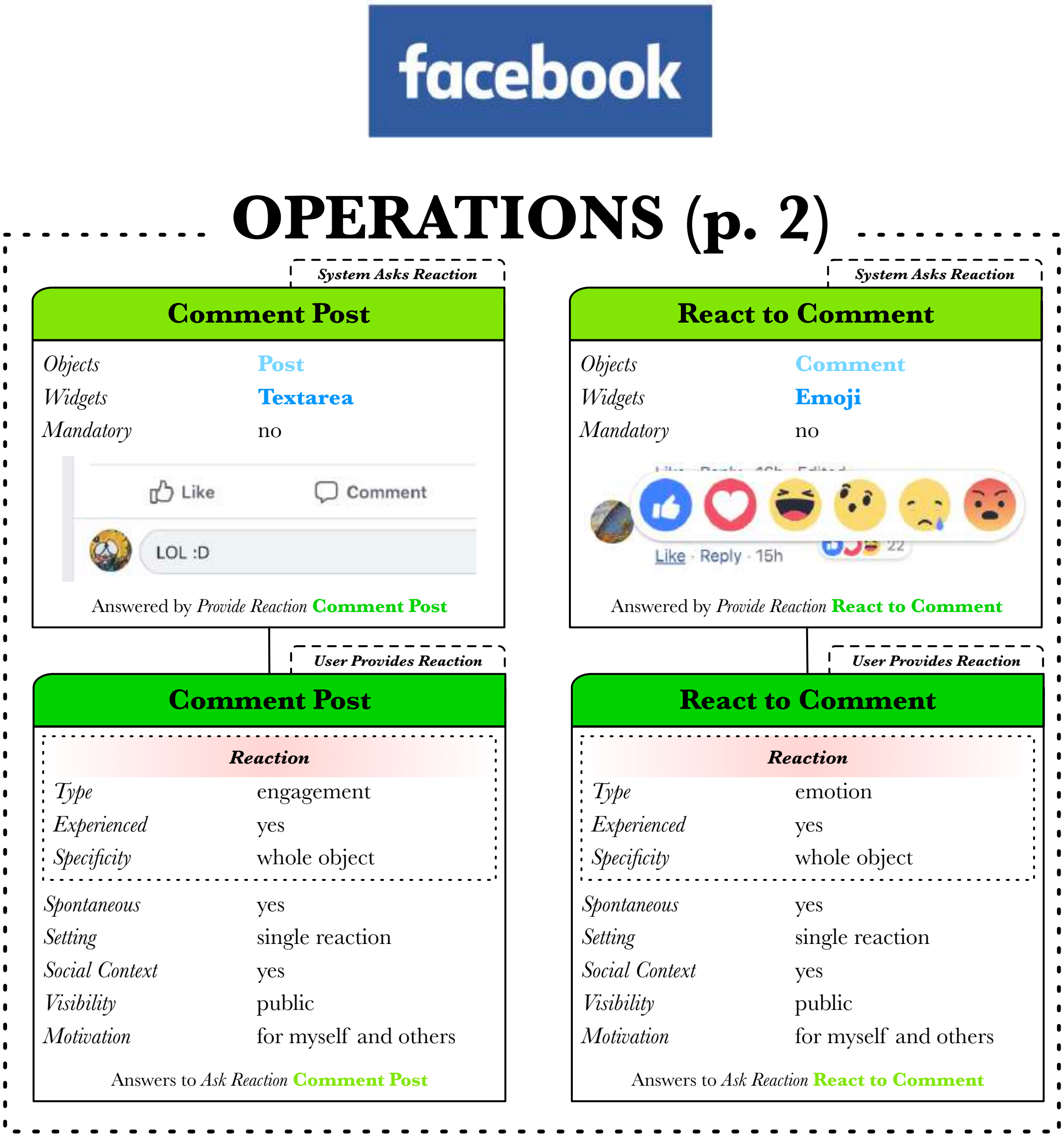


Figure A11. Facebook representation according to the UpRISE model: *operations (2)*.

OPERATIONS (p. 3)

System Asks Reaction

Reply to Comment

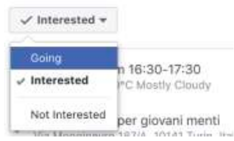
Objects	**Comment**
Widgets	**Textarea**
Mandatory	no

Answered by *Provide Reaction* **Reply to Comment**

System Asks Reaction

React to Event

Objects	**Event**
Widgets	**Event Partecipation**
Mandatory	no



Answered by *Provide Reaction* **React to Event**

User Provides Reaction

Reply to Comment

Reaction

Type	engagement
Experienced	yes
Specificity	whole object

Spontaneous	yes
Setting	single reaction
Social Context	yes
Visibility	public
Motivation	for myself and others

Answers to *Ask Reaction* **Reply to Comment**

User Provides Reaction

React to Event

Reaction

Type	engagement
Experienced	yes
Specificity	whole object

Spontaneous	yes
Setting	single reaction
Social Context	yes
Visibility	public
Motivation	for myself and others

Answers to *Ask Reaction* **React to Event**

Figure A12. Facebook representation according to the UpRISE model: *operations (3)*.

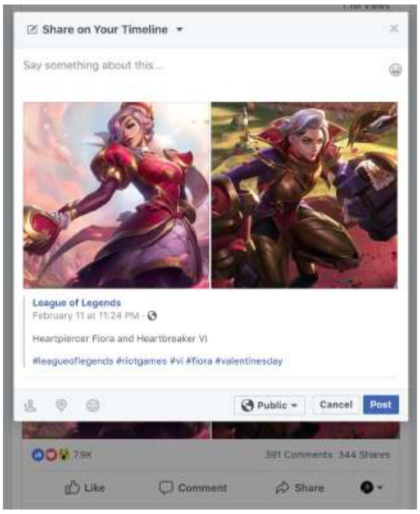
facebook

OPERATIONS (p. 4)

System Asks Reaction

Share Post/Page

Objects	**Post** or **Page**
Widgets	**Share**
Mandatory	no



Answered by *Provide Reaction* **Share Post/Page**

User Provides Reaction

Share Post/Page

Reaction

Type	engagement
Experienced	yes
Specificity	whole object

Spontaneous	yes
Setting	single reaction
Social Context	yes
Visibility	customizable
Motivation	for myself and others

Answers to *Ask Reaction* **Share Post/Page**

System Asks Reaction

Like Page

Objects	**Page**
Widgets	**Like**
Mandatory	no

Answered by *Provide Reaction* **Like Page**

User Provides Reaction

Like Page

Reaction

Type	evaluation
Experienced	yes
Specificity	whole object

Spontaneous	yes
Setting	single reaction
Social Context	yes
Visibility	public
Motivation	for myself and others

Answers to *Ask Reaction* **Like Page**

Figure A13. Facebook representation according to the UpRISE model: *operations (4)*.

OPERATIONS (p. 5)

System Asks Reaction

Recommend Place

Objects	**Page**
Widgets	**Recommend Place**
Mandatory	no

Answered by *Provide Reaction* **Recommend Place**

System Provides Response

Recommendation

Response	**Recommendation**
Timing	late
Proactive	yes

User Provides Reaction

Recommend Place

Reaction

Type	engagement
Experienced	yes
Specificity	whole object

Spontaneous	yes
Setting	single reaction
Social Context	yes
Visibility	customizable
Motivation	for myself and others

Answers to *Ask Reaction* **Recommend Place**

Figure A14. Facebook representation according to the UpRISE model: *operations (5)*.

A.2. XML Schema for the UpRISE model

The XML Schema for the UpRISE model is available at: `http://www.di.unito.it/~vernerof/uprise/uprise.html` and is displayed in a concise tree view in Figure A15.

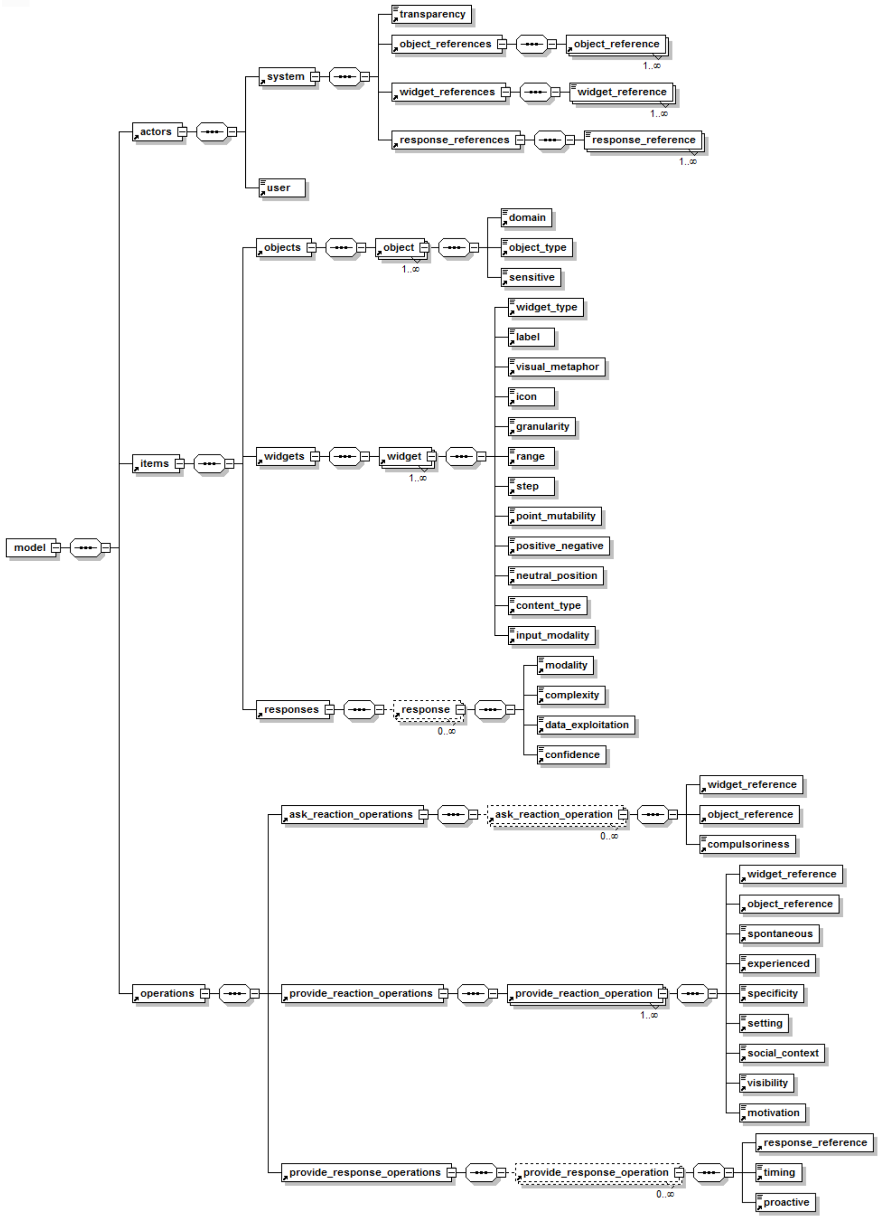


Figure A15. XML Schema for the UpRISE model: tree view