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About time

A motivation-based complementary framework for temporal dynamics in Web personalization

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Abstract

Purpose – The purpose of this paper seeks to develop a motivation-based complementary framework for temporally dynamic user preferences to facilitate optimal timing in web personalisation. It also aims to highlight the benefits of considering user motivation when addressing issues in temporal dynamics.

Design/methodology/approach – Through theory, a complementary framework and propositions for motivation-based temporal dynamics for further testing are created. The framework is validated by feeding back findings, whereas some of the propositions are validated through an experiment.

Findings – The suggested framework distinguishes two ways (identifying/learning and shifting) of using a motive-based approach to temporal dynamics in web personalisation. The suggested outcomes include enhanced timing in matching current preferences and improved conversion. Validation measures predominantly support both the framework and the tested propositions. The theoretical basis for the approach paves a path towards refined psychological user models; however, currently on a complementary level.

Research limitations/implications – While the framework is validated through feeding back findings, and some of the propositions are validated through basic experimentation, further empirical testing is required.

Practical implications – A generalised approach for complementing personalisation procedures with motivation-based temporal dynamics is offered, with implications for both user modelling and preference matching.

Originality/value – This paper offers novel insights to web personalisation by considering the in-depth effects of user motivation.

Keywords Timing, Temporal dynamics, Fundamental motives framework, Preference matching, Web personalization

Paper type Conceptual paper

Introduction

Web personalisation requires the matching of user preferences by delivering the right option at the right time (Tam and Ho, 2005). However, when is the time right? Despite its centrality to the practice of web personalisation (Koren, 2010), timing – or temporal dynamics – has received insufficient attention in the literature (Ho *et al.*, 2011; Huang

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and Zhou, 2018; Salonen and Karjaluoto, 2016). Few attempts have been made to either effectively produce a real-time model that considers the effects of changing intentions (Ding *et al.*, 2015) and cognitive styles (Hauser *et al.*, 2014) or to develop methods for adapting to these. We wish to continue this development by expanding on the psychology of shifting preferences.

Temporal dynamics in web personalisation refers to user preferences changing with time. Here, time is primarily a context for interaction (Ho *et al.*, 2011), which could be termed either situational or contextual time. The element of timing presents many problems for web personalisation practices. For example, because preferences are in flux (Simonson, 2005), timing requires an understanding of the user's immediate context, which is often different from that of the long-term user profile (Jannach *et al.*, 2015). In addition, understanding, predicting and activating such contextual effects require refined psychological models (Salonen and Karjaluoto, 2016). Matching preferences can also become increasingly difficult when no prior user profile exists. In such cases, recommendations are based on guesses at best (Johar *et al.*, 2014). Finally, it is difficult to grasp rapid changes using currently available approaches (Ding *et al.*, 2015).

Previous studies that have investigated timing effects in web personalisation and web adaptation have been fruitful (Bodoff and Ho, 2014; Bogina *et al.*, 2016; Ding *et al.*, 2015; Hauser *et al.*, 2009, 2014; Ho *et al.*, 2011; Hong *et al.*, 2012; Jannach *et al.*, 2015, 2017; Koren, 2010; Lambrecht and Tucker, 2013; Li *et al.*, 2014; Pereira *et al.*, 2018; Urban *et al.*, 2013). However, these studies predominantly focussed on long-term changes rather than on having more immediate effects (Hong *et al.*, 2012) built upon a rational view of user behaviour (Ho *et al.*, 2011) or neglected contextual factors (Li *et al.*, 2014). Therefore, a framework that also captures more immediate contextual effects is needed.

Although recent advances have been made towards effective real-time modelling (Ding *et al.*, 2015; Hauser *et al.*, 2014; Jannach *et al.*, 2015, 2017; Pereira *et al.*, 2018), these models have mostly been built via simple psychological modelling. For instance, Ding *et al.* (2015) found encouraging results for their real-time intent-based model, which was based on the stimulus-organism-response (SOR) framework. However, the SOR framework does not provide specific answers regarding when, why and how a certain stimulus is likely to affect a user's choices. Similarly, Hauser *et al.* (2014) based on their real-time approach on cognitive styles, which could possibly benefit from considering the interplay between motivation and preferences. Hence, we wish to provide the first steps towards more refined psychological models to enable an enhanced psychological fit in web personalisation.

Although preferences are state dependent (Zhang, 2013) and motivation is driven (Griskevicius and Kenrick, 2013), motivation-based approaches have been lacking in the web personalisation literature (Salonen and Karjaluoto, 2016). While Pappas *et al.* (2017) and Huang and Zhou (2018) have recently found encouraging results based on both complexity theory and uses and gratification theory, we envision a more effective approach by using a motivational framework that:

- fully acknowledges chronic (long-term) and situational (short-term) effects; and
- provides a detailed list of expected behavioural tendencies.

Therefore, we suggest a motivation-based approach that relies on the fundamental motives framework (FMF) (Griskevicius and Kenrick, 2013; Kenrick *et al.*, 2010a, 2010b). In this article, we suggest that applying the FMF to web personalisation enables both explanatory advances and practical inferences as follows:

- incorporating motives into the personalisation process may enhance the current understanding of contextual effects;
- via the framework, user preferences and choices can be predicted when the currently active motive is estimated. Thus, it provides a tool for addressing temporal dynamics in web personalisation;
- it may be possible to activate a given motive by managing cues in the given web environment, which could yield persuasive benefits (Kaptein *et al.*, 2015); and
- the framework may facilitate active learning by predicting motivational effects based on exposure to web content (Fernández-Tobías *et al.*, 2016 for a personality-based approach).

Furthermore, we believe that a motivation-based approach can complement the current understanding of what, for instance, click-stream analysis reveals about user preferences (Ding *et al.*, 2015; Montgomery *et al.*, 2004). The benefit of our suggested approach is that it is possible to learn not only the goal of the user but also the function of the goal and to expect different behavioural tendencies based on that knowledge (Griskevicius and Kenrick, 2013). Understanding which of these behavioural tendencies are likely to manifest and when these manifestations will occur is essential for effectively timed personalisation. While the FMF can provide only a complementary tool for solving timing issues in web personalisation, even an incrementally better match with the user's motivation could yield considerable benefits.

We also raise the possibility of using motivation to facilitate active learning and the use of persuasiveness in personalisation. Motivation-based active learning could be used in a similar fashion to show how personality has helped mitigate the kick-starting problem of collaborative filtering (Tkalcic and Chen, 2015; Zhang and Zhao, 2017). While personality is a stable construct (Cobb-Clark and Schurer, 2012), motivation manifests both chronically and situationally (Kenrick *et al.*, 2010a, 2010b), which is more aligned with temporally dynamic preferences. Furthermore, an approach based on the FMF could facilitate determining, which persuasive strategies will be most effective (Kaptein *et al.*, 2015) because preferences can be predicted through motivation (Griskevicius and Kenrick, 2013; Ho and Lim, 2018).

This study contributes to the web personalisation discussion in three significant aspects and is the first to address many of the inherent issues. We firstly provide a systematic but non-restricting motive-based framework for temporal dynamics in web personalisation that is applicable to both short- and long-term timing in personalisation processes. Our model is not intended to be a standalone for determining psychological fit (i.e. matching recommendations with psychological profiles) in web personalisation. However, several benefits make the FMF a good introductory and complementary model because psychological fit has not been considered extensively before in the temporal dynamics' literature. The framework is validated through feeding back findings by interviewing expert practitioners.

We secondly suggest the testing of several practical propositions in future research, which will deepen our understanding of the interplay among preference matching, timing and motivation. Insights arising from these propositions should be applicable beyond timing issues in web personalisation. The propositions are validated through a simulated purchase case experiment.

Finally, we highlight possibilities for applying motivation-based temporal dynamics to a variety of instances, such as active learning and persuasive strategies.

Temporal dynamics in web personalisation

The area of temporal dynamics has been neglected prior to recent developments in the web personalisation literature (Bogina *et al.*, 2016; Ding *et al.*, 2015; Hauser *et al.*, 2014; Hauser *et al.*, 2009; Ho *et al.*, 2011; Ho and Tam, 2005; Hong *et al.*, 2012; Jannach *et al.*, 2015, 2017; Lambrecht and Tucker, 2013; Li *et al.*, 2014; Pereira *et al.*, 2018; Urban *et al.*, 2013). Despite clear benefits and rising interest, temporal dynamics remains an understudied dimension of web personalisation (Ho *et al.*, 2011; Huang and Zhou, 2018; Salonen and Karjaluoto, 2016).

The use of temporal dynamics in web personalisation represents a multi-faceted concept. A simple example of temporal dynamics is how a user living in the northern region of the globe and looking for outdoor footwear likely prefers winter boots in December but not in July. If we consider the scope of temporal dynamics, this situation is an example of a long-term approach, which considers the long-term profile that is built for repeat users and often results in catering to either incremental changes in established needs or patterns of lifecycle shifts. Such long-term or lifecycle-based approaches have been shown to have a significant positive effect on personalisation results (Hong *et al.*, 2012).

However, user preferences show variation, are dependent on the user's state (Zhang, 2013) and – at least partially – are short term in nature (Griskevicius and Kenrick, 2013; Simonson, 2005). Thus, a more immediate approach to determining shifted preferences has intuitive appeal. For this purpose, we categorise both mid-term and short-term approaches here. By mid-term approaches, we mean temporal dynamics that can be primarily applied to sessions in short proximity to one another. A good example of such an approach is Lambrecht and Tucker's (2013) study on how the particular stage of the decision making process affects whether the re-targeting of banner ads is effective. Moreover, our focus is on the second possibility: the personalisation that occurs either within the short term or within a single session. Examples of such an approach are few but growing (Ding *et al.*, 2015; Hauser *et al.*, 2009, 2014; Urban *et al.*, 2013). Hence, temporal dynamics in web personalisation can address the currently active user preference (which is subject to both long- and short-term changes) through personalisation processes. We summarise the key literature on temporal dynamics in web personalisation and web adaptation in Table I.

Although long- and mid-term approaches provide other interesting insights, short-term approaches are required to determine what the user wants right now. For example, users choose high-calorie foods when e-shopping while hungry (Nederkoorn *et al.*, 2009). This immediate effect is likely to manifest, even if the long-term user profile contradicts it. However, there is a need for more research regarding immediate effects, especially in combining short-term behaviours with long-term profiles (Ding *et al.*, 2015). Moreover, although context awareness in recommender systems has been extensively researched, the existing studies rarely consider contextual issues from the psychological perspective (Adomavicius and Tuzhilin, 2011). Thus, a complementary approach based on a refined psychological model could enable new insights.

Why should we consider motivation?

Timing does not simply rely on knowing when and how to act; it also increasingly depends on the approach. Therefore, finding an effective approach for user modelling is a foundational question in web personalisation (Krishnaraju and Mathew, 2013). Recent efforts to map and model the emotional aspect of user behaviour have been highlighted (Kwon and Lee, 2014). In this article, we suggest that motivation could be made the reference point for understanding user preferences.

Several dimensions of motivation make it valuable to temporal dynamics in web personalisation. For example, web personalisation is about matching preferences (Tam and Ho, 2005) and motivation is a key driver of preferences (Kenrick *et al.*, 2010a). Motivation and

Table I.
Summary of the key literature for temporal dynamics in web personalisation and web adaptation

Source	Approach	Application area	Focus of interest	Timescale	Key finding(s)
Ho and Tam (2005)	Matching stated preferences	E-commerce	Stage of decision making	Mid- to short-term	Personalisation is effective when users form their consideration sets but not after the decision has been made
Hauser *et al.* (2009)	Matching user cognitive styles based on click-stream	Website (conversion)	Psychological fit	Short-term (long-term)	Adapting to match cognitive styles boosts conversion considerably
Ho *et al.* (2011)	Matching simulated preferences/click-stream	E-commerce	Timing of showing personalised content within the visiting period	Short-term	The effectiveness of personalisation is a question of optimising the early presentation of recommendations and the quality of the recommendations
Hong *et al.* (2012)	Collaborative filtering coupled with short- and long-term profiles	E-commerce	Stage of lifecycle	Long-term	Incorporating lifecycles into recommendations boosts performance
Lambrecht and Tucker (2013)	Dynamic re-targeting	Banner advertising	Stage of decision making	Mid- to long-term	Dynamic re-targeting is only effective if it fits a user's stage of decision making: high-level information is effective in the early stages; detailed information is effective in later stages. preferences narrow
Urban *et al.* (2013)	Matching user cognitive styles based on click-stream	Banner advertising	Psychological fit and stage of decision making	Short-term	Improved banner effectiveness goes beyond traditional targeting
Hauser *et al.* (2014)	Matching user cognitive styles based on click-stream	Website (conversion)	Psychological fit and stage of the visit	Short-term (Long-term)	Morphing to match a user's cognitive style increases conversion
Li *et al.* (2014)	Content-based filtering coupled with short- and long-term profiles	Online news	Variance between long-term and short-term profiles	Mixed	Combining long-term and short-term profiles increases personalisation effectiveness
Ding *et al.* (2015)	Real-time backward learning with dynamic learning	E-commerce	Learning user real-time intent based on browsing behaviour and tested the effectiveness of marketing and web stimuli	Short-term	Intent-based website transformation decreases shopping cart abandonment and increases conversion

the ensuing user mindsets also operate and yield insights regarding both chronic (long-term) and situational (short-term) effects (Rucker and Galinsky, 2016), which are optimal for temporal dynamics that combine long-term and short-term profiles. For example, while approaches based on personality (Fernández-Tobías *et al.*, 2016; Tkalcic and Chen, 2015) have been fruitful, personality is a stable construct (Cobb-Clark and Schurer, 2012) that cannot be applied to short-term preference shifts. Furthermore, the explanatory power of chronic fundamental motivation may exceed that of the Big Five personality factors (Neel *et al.*, 2016). A motivation-based approach could then facilitate active learning of both long-term and short-term preference shifts and mitigate the cold-start problem – as measures of personality have done (Fernández-Tobías *et al.*, 2016; Tkalcic and Chen, 2015) – but offer a new and perhaps improved source of accuracy for user profiling. In addition, considering that motivation shifts preferences (Griskevicius and Kenrick, 2013), the appeal of various persuasive approaches is likely to differ based on the active motive (Kaptein *et al.*, 2015; Tam and Ho, 2005). A motivation-based approach for persuasion could be used similarly to how mood congruence can be used to predict unpredictable purchases (Ho and Lim, 2018). Finally, an in-depth approach to motivation in temporal dynamics in web personalisation could complement our current understanding of contextual effects. To date, contextualisation has been based on rather simple factors and rational models (Adomavicius and Tuzhilin, 2011). Additionally, the approach in temporal dynamics has relied on rather basic psychological models, such as the SOR (Ding *et al.*, 2015). While the SOR model is well-established, it is limited at the level of user mindsets (Murphy and Dweck, 2016; Rucker and Galinsky, 2016). Therefore, it lacks more specific answers regarding when, why and how a certain stimulus is likely to affect a user's choices. We propose that a more advanced approach could offer at least a heuristic value in determining contextual effects. Despite the various potential advantages, such in-depth motivation-based approaches have rarely been considered in web personalisation (Salonen and Karjaluoto, 2016). We thus, aim to provide an introductory method for such modelling that complements the state-of-the-art approaches.

To address the identified issues, we offer the FMF (Griskevicius and Kenrick, 2013) as a promising framework and an example of refined psychological models on the level of user mindsets (Rucker and Galinsky, 2016). Although the importance of understanding user motivation may be obvious, the link between ancestral goals (see below) and modern web personalisation may seem unclear. We completely agree that our approach is not suitable for a standalone model for temporal dynamics, but we believe that it carries considerable potential when combined with other approaches. We will show that this framework could be a viable starting point for motivation-based web personalisation for the following reasons:

- it provides explanatory power to both long- and short-term preference shifts, which is essential for effective timing;
- it predicts contextual effects in ways that other motivational frameworks do not; and
- it is built upon tenets that can be operationalised into specific, valuable hypotheses.

The key benefit is that, while current personalisation approaches rely on simple behavioural tracking ("the best predictor of future behaviour is past behaviour"), the FMF predicts that a user may behave inconsistently based on the active motive, and it facilitates both the prediction and estimation of these effects.

Notably, other motivational approaches could be effectively used in temporal dynamics for web personalisation. For instance, regulatory focus theory (Higgins, 1998) and its offspring – the concept of regulatory fit (Avnet and Higgins, 2006) – offer simple alternatives. However, we expect the FMF to provide a broader set of user behaviours (Griskevicius and Kenrick, 2013) and a more elaborate guide to the complexities of user preference shifting. Similarly, uses and gratifications theory is a viable approach to timing (Huang and Zhou, 2018) in a general sense, but the FMF can potentially go deeper into the study of the mechanisms of user preference shifting. Determining which of the many potential motivation-based approaches is best in practice requires testing and consideration of the application area. For our theoretical purposes, we find the FMF suitable due to multiple factors, which are discussed in more detail below. To narrow our focus regarding application areas, we will use product recommendations and promotions as more specific examples of interest for the remainder of this article. Many of the expected behavioural mechanisms in each motive class have more established touchpoints that are related to product recommendation and promotion issues (Griskevicius and Kenrick, 2013) compared to, for example, personalisation in e-learning, in which the focal process is different, and thus, may require a different approach (Salonen and Karjaluoto, 2016).

Fundamental motives framework

Based on the principles of evolutionary psychology (Confer *et al.*, 2010 for general evolutionary psychology; Durante and Griskevicius, 2016 for consumer behaviour; Kock, 2009 for information systems research), the FMF (Griskevicius and Kenrick, 2013; Kenrick *et al.*, 2010a, 2010b) posits that modern consumer motives have been shaped and continue to be affected by evolutionary challenges. At the root level, evolutionary challenges involve survival and reproduction, but they manifest themselves through a number of mediating motives. The FMF distinguishes but is not restricted to the following seven motives: evading physical harm, avoiding disease, making friends (or affiliation motive), attaining status, acquiring a mate, keeping a mate and caring for family (Griskevicius and Kenrick, 2013). Each motive is expected to result in predictable behavioural tendencies (Griskevicius and Kenrick, 2013, p. 376 for a list of behavioural tendencies that correspond to each motive class).

The FMF focusses on ultimate rather than proximate motives (Tinbergen, 1963); hence, a user is expected to have multiple concurrent motives that drive behaviour on different levels (Griskevicius and Kenrick, 2013). A user may have many proximate motives, such as having a fast, red car from a well-known brand (e.g. Ferrari). These “surface” motives relate to fulfilling one fundamental motive – mate acquisition – through conspicuousness. Notably, although users may be more consciously aware of their proximate motives, they are rarely aware of their choices on a fundamental level (Griskevicius and Kenrick, 2013).

In web personalisation, these insights are essential. For example, many true needs may go unnoticed if only proximate features are considered. With this in mind, should web personalisation simply provide different choices of red dresses or should it seek to understand the willingness to stand out in that given space of time? Using the FMF may enable the latter, deeper approach. Additionally, the number of proximate motives is enormous. While matching such a scale of preferences is difficult, the FMF focusses on the roots of the proximate motives, and can thus, condense the number of factors to a workable level. Although the task and the difficulty of linking proximate motives with likely fundamental motives remain, the FMF provides a manageable starting point.

Within the FMF, motives direct attention, memory and social inferences in both functionally specific (Kenrick *et al.*, 2010a) and unconscious ways (Griskevicius and Kenrick, 2013). For example, when the mate acquisition motive is active, men (but not women) – as evolutionary principles suggest – prefer products and promotional messages that highlight uniqueness (Griskevicius *et al.*, 2009). With such extensions, the FMF distinguishes itself from many other comparable approaches. Next, we consider how the main tenets of the framework apply to web personalisation.

General tenets for fundamental motives framework-based product recommendation and promotion in web personalisation

While other motivational theories may be more prominent, there are some distinct benefits of using the FMF in web personalisation. Regarding temporal dynamics in product recommendation and promotion, four general tenets of the FMF are essential as follows:

(1) *Tenet 1*: A fundamental motive can be activated by either external or internal cues (Kenrick *et al.*, 2010a).

(2) *Tenet 2*: The currently active motive shapes preferences (Griskevicius and Kenrick, 2013).

(3) *Tenet 3*: The currently active motive guides decision processes (Griskevicius and Kenrick, 2013).

(4) *Tenet 4*: Although all fundamental motives can be activated with immediacy, one or a few motives are expected to manifest more chronically than others regarding individual differences (Neel *et al.*, 2016).

Tenet 1

The first tenet highlights the interactivity between internal and external factors that shape motive activation. Internal cues include hormonal changes that shift preferences for products (Durante and Arsena, 2015), per evolutionary guidelines. More importantly, users are unconsciously primed by environmental cues, which lead to preferences and decisions based on the environment (Dijksterhuis *et al.*, 2005). As suggested by a pool of literature that is substantially deeper than the few examples cited here, the case for the evolutionary driving mechanisms of human and consumer behaviour is solid (Durante and Griskevicius, 2016).

With that said, how does the supposed motivational driving mechanism function in an online environment? For instance, product choice may be affected by website backgrounds and pictures (Mandel and Johnson, 2002). Thus, elements in the web environment may be managed to activate a chosen motive, although simply being in the presence of external cues does not completely dictate the activation of a motive; other internal processes may be more salient. For practical purposes, the external cues are suggested here as the primary concern of short-term web personalisation processes.

What the first tenet means for web personalisation is that the user's interaction with web content can be used to estimate an active motive in two ways:

(1) by rating how saturated the content is with motive-eliciting cues and how exposed the user is to those cues; and

(2) by predicting the currently active motive via click-stream analysis.

Each click is estimated to indicate the active motive, which can be estimated by the motive congruence of choices. For example, reading a newspaper article online with pictures of attractive Hollywood stars should activate the mate acquisition motive, whereas reading about violence in the neighbourhood should activate the self-protection motive (Griskevicius *et al.*, 2009). Conversely, if the user makes the choice to read about these topics, that choice would predict the prevalence of a congruent motive.

Tenet 2

The second tenet directly reflects the goal of web personalisation – preference matching. Specific changes in cognition and predictable shifts in preferences occur in relation to an active fundamental motive (Kenrick *et al.*, 2010a). In practice, although the risk of buying a non-functional product generally does not threaten a user's well-being in modern society, due to deep-seated mechanisms, users form preferences and approach choices as if those choices might pose a threat through *unconscious* processing (Griskevicius *et al.*, 2009). Further, Simonson (2005) proposes that offers that fit the current evaluation context will be perceived as superior. We suggest that motivation is a key factor in determining the context of a user's choice. The shifting nature of preferences per an active motive class complements other general preference studies in web personalisation (Koren, 2010) that emphasise contextual effects on preferences. Simonson (2005) also suggests that the effect of motivation-shaping preferences is expected to be stronger for users who perceive the context to be credible and who have not developed strong prior preferences. Notably, the FMF suggests that only one fundamental motive is active at a given time, which makes it possible to predict changes in preference. Such a capacity could enhance prior efforts towards the timing of web personalisation (Ho *et al.*, 2011). Likewise, prior strong preferences are expected to reign supreme (see Tenet 4 below) as long as the underlying motive remains active without changing to another functionally polarising motive for preferences.

Tenet 3

As the Tenet 3 claims, user decision making processes are also guided by motivational factors. Here, we wish to highlight that the information processing of the product or promotional information may differ per the active motive class. For instance, when making economic decisions, people become loss averse when their self-protection motives are active, but especially men become significantly less so when mate acquisition motives are active (Li *et al.*, 2012). This finding emphasises the regulatory focus of users regarding whether they are in either a promotional state or a prevention state (Avnet and Higgins, 2006). As suggested by Avnet and Higgins (2006), users experience value when an offer is in line with their currently active state. The FMF may offer a practical tool for web personalisation that enables value through this motivational fit. In the web personalisation realm, such a cue (or psychological) fit has already been shown to increase users' willingness to pay (Benlian, 2015).

Tenet 4

The Tenet 4 suggests that fundamental motives are not always in a flux; rather, either one or a few motives manifest themselves more chronically based on individual differences (Neel *et al.*, 2016). Each motive is active in each individual at a given time, but individuals differ in their proclivity to manifest a given motive. The identification of a chronic motive opens an avenue for long-term profiling. In the case of product choice, previous shopping and/or browsing history could reveal, which features the user prefers, especially, if the history is analysed for motive congruence. This long-term motive-based profile would then function as a baseline in web personalisation processes, including more immediate approaches (Li *et al.*, 2014), where the chronic motive could be used to predict susceptibility to cues for that motive. To emphasise this aspect, the FMF may be able to enrich user profiling by providing a tool for assessing prior behaviour and/or product choice from a motivational perspective (Ding *et al.*, 2015; Montgomery *et al.*, 2004). Such a tool could facilitate determining the meaning of motivation when the user, for example, chooses either the most or the least expensive product (Han *et al.*, 2010).

The key takeaway from the FMF is that both user preferences and decision making follow predictable tendencies based on the active motive. Hence, the use of the FMF comes from not only the understanding that a self-protection motive might lead to a preference for safe products but also the cognitive processes that seek to decrease risk, even in seemingly unrelated choices. For a complete list of expected behavioural tendencies for each active motive, see Griskevicius and Kenrick (2013, p. 376).

Priming for motivational effects

One of the distinguishing features of the FMF is its capacity to account for behavioural change according to cues in the (web) environment on a deeper level than those that are often considered in web personalisation (Adomavicius and Tuzhilin, 2011). In addition to, for example, motive-congruent click-stream analysis, it is important to understand that, to some extent, the choices that users make are due to environmental cues. Hence, we will consider the role of priming the produced motivational effects in users in more detail.

Priming may also guide behaviour. Notably, behavioural priming can have even stronger effects than semantic priming because of its ability to activate downstream constructs, such as goals (Wheeler *et al.*, 2014). Primed consumer behaviour shows signs of automated goal pursuit (Dijksterhuis *et al.*, 2005), which gives credence to the tenets of motive-based preference shifting in accordance with environmental factors, as suggested by the FMF. Buying decisions are strongly affected by the environment, even though the effect is unconscious (Dijksterhuis *et al.*, 2005). Similarly, online channels may include cues that shift users' willingness to pay (Benlian, 2015). Yet, it is important to consider that priming cannot dictate user behaviour because it has no direct control over either judgment or behaviour (Loersch and Payne, 2014). To illustrate, one prime can have different effects based on the context (Wheeler and Berger, 2007). Therefore, applying the FMF may provide insight regarding what specific effects occur.

Priming effects are especially strong when the associative power of the prime is high (Dijksterhuis *et al.*, 2000). However, as demonstrated by Wheeler and Berger (2007), it is essential to consider the context as well because it may divert users from stereotypical actions, and thus, either prevent or invert the expected effect.

Based on findings in other related contexts, as described above, understanding prime-to-behaviour effects is likely to be beneficial for advancing the field of web personalisation. Importantly, how the many visual and/or semantic cues shape preferences and the subsequent motive-based behaviour have not been comprehensively considered. Using the FMF may be suited for such a task.

Propositions for motive-based temporal dynamics

Here, we summarise our theoretical basis thus, far in the form of actionable propositions for future research. Our primary argument is that the current understanding of preference shifting and formation in web personalisation can be enhanced using a complementary motive-based approach. The suggested propositions should be tested with empirical data beyond our partial empirical validation.

While a motive-based approach should be beneficial for web personalisation in general, our chief application area for this approach is in the temporal dynamics of high-involvement product recommendation and promotion. Regarding temporal dynamics in web personalisation, we suggest that accurate timing is unlikely if a motivation match is not found. Not all the propositions listed consider temporal dynamics directly; instead, they contribute the more nuanced perspective of preference shifting that underlies our suggestions for temporal dynamics. Table II summarises the propositions, which are individually discussed in the section that follows.

Table II.
Propositions for motive-based temporal dynamics

P1	Preference matching will be greater when personalisation results match the drivers of the currently active fundamental motive
P2	A given fundamental motive can be activated in the web environment through external cues, such as the following: A: visual cues (e.g. website background picture) B: semantic cues (e.g. newspaper article content) C: auditory cues (e.g. music)
P3	The greater the user's awareness of the cues, the stronger the priming effect for the activation of a fundamental motive
P4	The higher the cultural congruence between the prime and any product or promotion features in relation to the drivers of the currently active fundamental motive, the stronger the priming effect and the preference match
P5	Regarding individual differences in chronic-like motives, users are more susceptible to cues for certain motives than others

The *P1* relies on the key assumption that motivation primarily dictates the direction of preferences. This assumption follows the tenets of the FMF (Griskevicius and Kenrick, 2013). In this view, preferences facilitate goal attainment, and thus, work as an intermediary for motives. Empirical evidence of this has been built through the use of promotional message preference shifts and economic decisions for each active fundamental motive (Griskevicius *et al.*, 2009; Li *et al.*, 2012). In the world of web personalisation, either a product or product message should be prioritised if it supports the attainment of the currently active motivational goal. For example, the popularity of products that are promoted as "unique" should increase when the mate acquisition motive is active in male users, and they should decrease when the self-protection motive is active (Griskevicius *et al.*, 2009).

The *P2* expands on the assertion that the user's current environment directs motive activation to secure the best fit (Griskevicius and Kenrick, 2013). These external cues can take many forms. Visual cues consist of background pictures, photos and video content that are consumed in the immediate session, whereas semantic cues are text content based. Furthermore, auditory cues, while possible, are rare in practice. The influence of motive shaping cues is expected to vary per the level of initial product knowledge, the confidence in the beliefs that are vested in the product knowledge and trust in the recommendation agents (Adomavicius *et al.*, 2013; Yin *et al.*, 2016). Thus, motive-eliciting cues do not work solely on priming effects; rather, they require broader predictions about the user. To conclude, through implicit ratings, web personalisation processes should become more aware of the motivation congruence of the elements with which the user interacts. Personalisation processes should also expect these elements to guide behaviour through motive-directing priming cues and to generate predictable changes in preferences. Using the FMF enables actionable inferences for this purpose.

The *P3* follows the findings by Lähteenmäki *et al.* (2015), who emphasise the importance of awareness in recognising the prime to ensure effective results. This does not mean that processing the prime would not, at least in part, be unconscious; the priming cue will instead have a stronger effect if it is consciously recognised. In the web environment, this statement implies that the priming effect is stronger when the user is more aware, for example, of a background picture, which means that more distinguishable pictures are more effective at priming.

The *P4* is based on findings regarding the relationship between associative strength and priming (Dijksterhuis *et al.*, 2000). Sassi *et al.* (2017) have called predicting the relevance of items in regard to contextual factors the next step in recommender systems. Here, we suggest that those priming cues that can be associated with attaining the motivational goal will show predictable preference shifting per the active fundamental motive. As discussed above, a sexy background picture may activate the mate acquisition motive in a male user. Additionally, such a picture is more likely to generate a preference for flashy cars than a carton of premium milk because flashy cars are more likely to be culturally recognised as increasing one's value in the mating market. Consequently, both the priming effect and the preference match are expected to be stronger when the associative power is stronger. If this proposition holds true, it should enable the identification of the currently active motive based on a click-stream analysis (Ding *et al.*, 2015; Montgomery *et al.*, 2004). It is more established that each user's choices may indicate his or her preferences, but linking these choices to motivation and building a temporal user profile by testing that link is new in web personalisation. Using such an approach could enable a new level of accuracy in matching fluctuating preferences.

The *P5* follows one of the FMF's tenets in expecting either one or a select few motives to manifest chronically, which will lead to individual user differences (Neel *et al.*, 2016). Hence, some users are more readily affected by cues that relate to a certain motive. The significance of this proposition for temporal dynamics in web personalisation is most notably in long-term profiling. Knowledge of prior motive-laden choices can be used to create a baseline, which can be validated as more data on the immediate session are gathered. While such an approach follows current practices, interpreting the data through motive congruence should reveal a greater variety of details regarding the user's preferences.

Validation of the propositions

A 1 (user type: male) $\times$ 2 (motivation: mate acquisition and self-protection) simulated purchase case experiment was created for an empirical test for *P1* and *P2*. For the experiment, a mock-up of a fictional e-commerce site selling men's T-shirts was built. The participants saw one product page featuring a rainbow-colored T-shirt. In addition to the product information, we placed a banner advertisement for either a dating company, featuring an attractive woman or for a security company, featuring an aggressive man. Both advertisements had the same copy text: "Life is full of chances". A pre-test (N = 136) based on an analysis of variance revealed that these banner ads were effective at priming the participants' motivation so that the dating company advertisement increased mate acquisition [$F(1,67) = 6.23, p < 0.05$] more than the self-protection group did, and the security company advertisement increased self-protection [$F(1,67) = 18.42, p < 0.01$] more than the romantic cue group did. For the motivation measurement, we used the same items as Griskevicius *et al.* (2009), which were combined into factor scores.

For the experiment, although we recruited 194 male participants via MTurk, 56 of them failed to correctly answer a manipulation check question, which left 138 participants. In the experiment, we asked participants to rate their attitude towards the rainbow-colored T-shirt on three adjective pairing items (bad-good, dislike-like and undesirable-desirable), which we combined into a factor score. An independent sample *t*-test was conducted to compare their attitudes towards the product in both the mate acquisition (dating ad) and self-protection (security ad) conditions. Our hypothesis, which was based on the behavioural tendencies of the focal motivators (Griskevicius and Kenrick, 2013), was that mate acquisition should drive a preference for the most eye-catching product. Support for this hypothesis was found; there was a significant difference in the scores for the mate acquisition ($M = 2.60$, $SD = 1.15$) and self-protection ($M = 2.10$, $SD = 1.29$) conditions and [t (134) = 2.33, $p = 0.02$]. These results provide support for *P1* and *P2*. The results further support that cues, such as banner ads, may be used to activate such motives. While the preliminary study confirmed the effectiveness of the priming cues, in the experiment, the values of this manipulation check remained in the non-significant region. This limitation may be due to the fact that participants answered other questions between priming and the manipulation check question, which was not the case in the pre-study. This may explain the difference in the priming effect between the pre-study and the experiment. We posit that, while support for the propositions that were tested was found overall, they must be empirically tested further.

For this additional testing, evaluating the role of the motivation-preference link is key, and at least three approaches are possible:

(1) Emphasis could be placed on how the user's chronic motivational disposition may predict preferences in online environments. This would facilitate the creation of a long-term user profile and a baseline for possible short-term preference shifts.

(2) Short-term effects could then be studied through, for example, click-stream analysis to measure whether preferences that are inferred from user choices in an online environment follow the expected preference shifting mechanisms (based on the FMF here). In practice, this requires categorising elements and content in the focal online environment, grading them on the motivational scale and making predictions regarding the expected motivation-preference link.

(3) The same approach for short-term effects could also be inverted and studied through the priming effects of the elements and the content in the focal online environment.

Thus, motivational grading of elements and content can be used for predicting possible shifts in a user's preference prior to gathering enough data to create a more established user profile. The expected mechanisms are based on priming effects.

When combined, these five propositions outline a possible new direction in temporal dynamics in web personalisation. A deeper understanding of motive-based preference shifts may reveal an actionable framework for more accurate timing as a complementary and introductory tool if the propositions hold true under the scrutiny of empirical testing.

Framework for product recommendation and promotion in web personalisation

We have thus far outlined how a motive-based approach, via following the FMF in our case, could be a valid complement for a temporal recommendation. Here, we distil our key points into an actionable framework for product recommendation and promotion based on the FMF. As illustrated in Figure 1, our framework follows a process orientation by depicting the activation of a motivational state as the starting point for a firm-initiated personalisation process for increased conversion. Following Sunikka and Bragge's (2012) claim that information gathering regarding users' preferences usually includes both user- and company-driven initiatives, our framework distinguishes both as active players.

The suggested framework focusses on the user in the first phase. The personalisation process may be company initiated, but the user must first reveal his or her preferences through his or her actions. In this framework, the currently active motive is the focal point that guides the following steps. As suggested above, a motive is activated through both internal and external factors. Internal factors include situational factors and stable chronic motives, which create opportunities for long-term profiling while possibly restraining the activation of other motives. The external factors include environmental cues that tend to take visual and semantic forms, which are more easily accessed by the company and can potentially be managed.

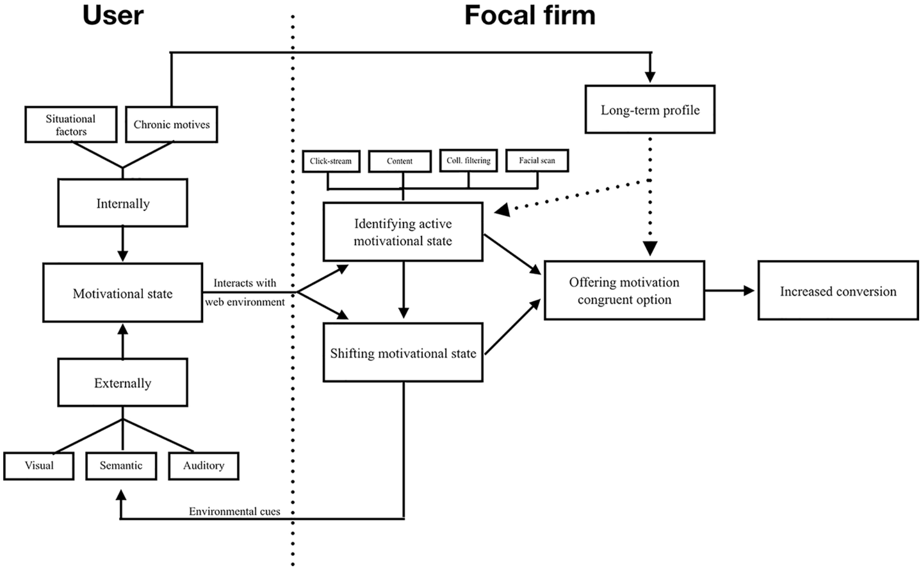

Figure 1. A process-oriented framework based on the FMF for temporal dynamics in product recommendation and promotion in web personalisation

The role of the focal firm is two-fold in the framework. In the second phase of the framework, the focal firm can seek to identify the currently active motive class via several methods (e.g. content analysis, collaborative filtering and advanced methods, such as facial scans) to assess the motive-eliciting cues in the environment and user profile features. The learned preferences may primarily be used to offer a motive congruent option. The firm may also seek to shift the motivational state through motive eliciting environmental cues (i.e. managing cues in the web environment to prime a motivational state).

The third phase further emphasises the need for understanding motivational factors in web personalisation. If a user's active motive has been successfully identified, the personalisation process should produce a choice selection that matches the drivers of the motive class. The framework suggests not only that a motive is identified but also that the focal firm must provide a motive-matching alternative.

Finally, following our main hypothesis, the fourth phase claims that, if the process of first identifying the user's active motive class and then providing a motive-matching alternative is successful, the end result is increased conversion. While motivation as the primary focus is novel in web personalisation, the process of seeking to connect user needs with company offerings is rooted in its foundation.

The suggested framework offers a combination of generality and specificity. The aim of the framework is to provide a systematic and actionable roadmap for considering motivation in web personalisation. The framework is non-restrictive in that it is inclusive of many inputs and open for additional inputs, but it is specified to product recommendations and promotion because these share similar goals. It may be possible to apply the framework elsewhere if similar goals are identified. Furthermore, the framework relies on the FMF, meaning that using the framework requires an evolutionarily educated approach, which is believed to provide a manageable number of motives and actionable inferences. However, if other motivation theories can provide these, then the suggested process may also be applicable to other motivation theories.

We suggest that, while the framework is complementary to current approaches and introductory, it reveals the possibility of inducing advanced psychological measures into the personalisation process. The framework is not flawless in terms of either scope or specificity, but it does provide an extensive basis for testing future avenues of psychological preference fits through the personalisation process.

Validation of the framework

To validate the framework, we used feedback findings by interviewing four expert practitioners in leading positions (Hollebeek *et al.*, 2016; Thomas and Tymon, 1982). The framework gained overall support from all involved experts. Specifically, they saw a number of benefits, such as that the framework offered new insights and opened avenues for a more detailed motivational approach. In addition, the option to either identify or shift motivational states received praise, and the discussion led to concrete application ideas in the case of one expert. Finally, the option to combine long-term motivational profiles with short-term profiles was considered useful. Overall, the feedback for the framework was encouraging. However, weaknesses were noted, which primarily addressed a potential lack of access to enough data. While large players were seen to have enough data to use the framework, it was noted that an avenue for smaller players to either access or purchase supporting data would be useful. One expert requested further elaboration of the expected behavioural tendencies of the motives. Interestingly, the framework was predominantly considered applicable to practice, but the experts' views differed regarding whether the framework is more applicable to promotion (digital marketing) or e-commerce, with both sides gaining support. Considering the feedback as a whole, the framework seems to offer a good foundation for the effort to complement current state-of-the-art practices with a deeper psychological fit based on motivation.

Conclusions

In a sense, all problems in web personalisation are timing problems. Knowing what a user usually wants represents a substantial achievement, yet true success lies in mastering the time component of "right now". Although contextual issues have been considered previously, motivation has rarely been identified as a key driver of preference shifts (and is thus, inseparable from temporal dynamics) in web personalisation. Additionally, it is novel to suggest an advanced psychological framework for preference dynamics that has both explanatory and predictive powers in web personalisation. However, this is only one possible complementary approach to determining how contextual factors play a role in temporally dynamic preference matching.

This study makes three contributions to the discussion of temporal dynamics in web personalisation:

- Several practical propositions, which address how motivation and preferences are linked and how the understanding of the interplay among preference matching, timing and motivation can advance the field and which could be tested in future research, are outlined.
- The above contributions are combined into a systematic but non-restrictive framework for temporal dynamics in product recommendation and promotion.
- Possibilities for applying motivation-based temporal dynamics to a variety of instances, such as active learning and persuasive strategies, are considered. In summary, this article has sought to not only indicate that motivation is an important dimension but also to provide a means of operationalising this knowledge in testable models, as suggested by our validation work. We believe that such extensions to current approaches serve as important complements to recent advances, such as those of Ding *et al.* (2015).

Our approach has several limitations, especially concerning the use of the FMF. Because the FMF is based on evolutionary psychology, it faces much of the same criticism (Confer *et al.*, 2010). In addition, because the FMF has not been designed for web personalisation, the applicability of each motive class may vary considerably, depending on the goal of the personalisation effort. For example, there are apparently more application areas for motives of mate acquisition and self-protection than there are for avoiding disease in the realm of web personalisation. More research on the effects of each motive, for which the suggested behavioural tendencies provide an excellent basis, is needed to determine how links between evolutionary drivers and online behaviours manifest (Kock, 2009). Finally, while the suggested framework for web personalisation offers novel and potentially significant advances in specific product recommendation and promotion situations, it may not be fruitful in all situations and for all products. For example, attempts to increase conversion for low-involvement products may be more difficult.

The theory, propositions, and framework that are included here all have solid bases in findings from other fields; however, we provide new insights into web personalisation. Further empirical testing beyond our validation efforts is required to cement the viability of the propositions and framework. If empirical support is found, web personalisation could begin to take steps towards using more sophisticated approaches to motivation-based temporal dynamics to enhance timing in web personalisation. The benefits of such a change should be considerable.

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