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Winner's regret in online C2C Auctions: an automatic thinking perspective

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Abstract. *While human beings embody a unique ability for planned behaviour, they also often act automatically. In this study, we draw on the automatic thinking perspective as a meta-theoretic lens to explain why online auction bidders succumb to both trait impulsiveness and sunk cost, ultimately leading them to experience winner's regret. Based on a survey of 301 online auction participants, we demonstrate that both trait impulsiveness as an emotional trigger and sunk cost as a cognitive trigger promote winner's regret. By grounding our research model in the automatic thinking view, we provide an alternative meta-theoretical lens from which to view online bidder behaviour, thus bolstering our current understanding of winner's regret. We also investigate the moderating effects of competition intensity on the relationships between the triggers of automatic thinking and winner's regret. Our results show that both trait impulsiveness and sunk cost have significant impacts on winner's regret. We also found that the relationship between these two triggers and winner's regret is moderated by competition intensity.*

Keywords: winner's regret, automatic thinking, trait impulsiveness, sunk cost

INTRODUCTION

Online consumer-to-consumer (C2C) auction sites have become increasingly popular since the founding of eBay in 1995. Millions of consumers visit online auction sites, and these sites have become an important channel for acquiring goods. While consumers can sometimes save money by using online auction sites, participating in online auctions often comes at a price. For example, consumers may find themselves spending more time than they would like to admit obsessively tracking the status of an auction. Worse yet, consumers may experience 'auction fever' and get so caught up with winning the auction that they end up experiencing 'winner's regret' (Ku *et al.*, 2005; Peters & Bodkin, 2007), defined here as winning the auction but with the subjective emotional assessment of having overpaid for the item. Prior research on auctions has often referred to winner's regret as the winner's curse (Foreman & Murhighan, 1996; Amyx & Luehlfing, 2006;

Malhotra, 2010; Adam *et al*., 2011). In this paper, we use the term winner's regret rather than winner's curse because winner's curse usually implies that the winning bidder pays more than an auction item is worth. The term winner's regret does not carry this connotation and is defined here as regret associated with the subjective emotional assessment of having overpaid for an item (regardless of whether the amount paid actually exceeds what the item is objectively worth). In order to gain a better understanding of *why* winner's regret occurs in online auctions, we introduce the perspective of automatic thinking as a meta-theoretical frame.

For a long time, economists have maintained that human behaviour is best described by the rational economic model, which basically holds that human beings are self-interested and capable of perfectly weighing the costs and benefits in every decision, thus enabling optimal choices (Ariely, 2008). Although human beings do, in fact, frequently make rational decisions, this does not necessarily mean that they do this all, or even most, of the time. In line with this argument, psychologists distinguish between two modes of thinking, one that is intuitive and automatic, and another that is reflective and rational (Thaler & Sunstein, 2009; Kahneman, 2011). Thaler & Sunstein (2009) refer to the first mode as automatic thinking. Automatic thinking provides a useful perspective for understanding the problem of winner's regret, because automatic thinking is rapid and instinctual (Bazerman & Moore, 2009). For example, when people get nervous during a flight that experiences turbulence or smile when they see a cute baby, they are using automatic thinking. In the online auction context, automatic thinking may help to explain why individuals experience auction fever and get so caught up in the auction process (Heyman *et al*., 2004; Ku *et al*., 2005).

Despite often-voiced concerns regarding the pitfalls of auction fever, the problem of winner's regret and why it occurs has not been examined from the perspective of automatic thinking. There are two types of triggers that result in automatic thinking: emotional triggers (Strack & Deutsch, 2004; Slovic *et al*., 2007; Hofmann *et al*., 2009) and cognitive triggers (Sloman, 1996; Kahneman, 2003; Klaczynski & Cottrill, 2004; Hofmann *et al*., 2009). Therefore, we believe that it is important to consider both emotional and cognitive triggers of automatic thinking in order to obtain a more complete understanding why winner's regret occurs. In this study, we thus explore two factors related to the automatic thinking that may influence winner's regret; trait impulsiveness, which is believed to be more emotional in nature, and sunk cost, which is believed to be more cognitive in nature. We chose these two factors because they are known to influence behaviour in related contexts. For example, escalation of commitment scholars have long suspected that sunk cost can create the kind of loss framing that is believed to promote escalation behaviour, and marketing researchers have pointed to impulsiveness as a trait that can influence retail buying behaviour. In addition to these two factors, competition intensity has been shown to affect bidding behaviour in online auctions, and we include it in our study to determine if it moderates the relationship between these automatic thinking triggers and winner's regret.

In summary, our aim is to better understand winner's regret by considering both emotional and cognitive triggers of automatic thinking and the role of competition intensity in this context. In doing so, we seek to answer two research questions:

1 To what extent do emotional and cognitive triggers of automatic thinking help us to predict winner's regret?

2 To what extent is the relationship between these automatic thinking triggers and winner's regret moderated by competition intensity?

While prior research has examined the impact of certain escalation drivers such as sunk cost on willingness to continue bidding (Park *et al.*, 2012) and how this can result in overbidding behaviour, we know of no research that has examined the effect of both cognitive and emotional triggers on winner's regret.[1] Thus, by addressing the previous research questions, we contribute to the current body of knowledge regarding individuals' behaviour in online auctions. From the standpoint of theoretical contribution, ours is the first study to draw on the lens of automatic thinking to examine two kinds of triggers (one cognitive and one emotional) that may contribute to winner's regret. Specifically, by investigating the impact of sunk cost and impulsiveness as well as the moderating role of competition intensity, we shed new light on the phenomenon of winner's regret in online auctions.

BACKGROUND

Online auctions and winner's regret

Online auctions are conducted over the internet and differ from traditional auctions in some important respects. First, online auctions remove the geographical constraints of traditional auctions, thus enabling worldwide participation (Ariely & Simonson, 2003). Second, online auctions can last for several days and can allow for asynchronous bidding, which makes them more flexible than traditional auctions and easier for people to participate in.

While online auctions are attractive in several respects, prior research has documented a number of problems associated with participating in them. These include psychological distress (i.e. anxiety, aggression, anger and depression), habitual usage, negative impacts on finances or social relations and dependency and withdrawal symptoms (Peters & Bodkin, 2007). One problem, which is the focus of our research, is winner's regret, defined here as regret associated with the subjective emotional assessment of having overpaid for an item (regardless of whether the amount paid actually exceeds what the item is objectively worth). The emotion of regret stems from the comparison of an actual outcome with a better outcome that might have resulted. In an online auction context, individuals may experience regret when they compare the actual price that they paid with their reservation price (i.e. the highest price a buyer is willing to pay).

While consumers may participate in online auctions to obtain a bargain, the reality is that in many instances they end up either overpaying for what they purchase or experience regret associated with the subjective emotional assessment of having overpaid for an item. Based on an analysis of 500 online auctions for compact discs and digital video discs, Ariely & Simonson

[1]Overbidding generally refers to situations in which individuals bid beyond their reservation price. Thus, overbidding need not necessarily result in winning an auction or in winner's regret, because many auction participants may engage in overbidding but only one person will win the auction. The distinction is important because winner's regret could influence an individual's willingness to use online auctions in the future.

(2003) reported that 98% of all winning bidders overpaid. Overpayment can be reduced by providing bidders with an easy means of checking the retail prices of goods. Based on a sample of 416 online auctions, Amyx & Luehlfing (2006) found that only 8.7% of the winning bidders overpaid when they were using auction sites that provided links to websites that allowed bidders to check the reference price of identical retail merchandise available for sale at the same website.

Naturally, when a bidder believes that he or she has paid too much for an item of uncertain value (Ku *et al*., 2005; Robert *et al*., 2011), regret can occur. A rational explanation for such regret can be formulated based on three assumptions: (1) while the average bidder may accurately estimate the value of the item up for sale in an auction, some bidders will underestimate this value and others will overestimate it; (2) the bidder who most greatly overestimates the value of the item will typically win the auction; and (3) the amount of overestimation will often be greater than the difference between the winning bidder's estimate of the value of the item and what s/he ultimately had to bid in order to acquire it (Amyx & Luehlfing, 2006). Under this view, regret occurs as a result of uncertainty regarding an object's value, and thus, bidders can be economically rational and still suffer regret when their information is poor.

Empirical evidence suggests that regret can arise even when bidders have perfect information (Ariely & Simonson, 2003; Amyx & Luehlfing, 2006), and thus, the behaviour that leads up to this can be viewed as irrational. Oh (2002) examined regret in consumer-to-consumer auctions and concluded that bidders do not necessarily behave in an economically rational way. Specifically, they tend to bid on items for the sheer enjoyment that is intrinsic in an online competition, rather than on the basis of utility in pure monetary terms. Furthermore, online auctions can produce an emotionally charged climate in which individuals try to outbid one another in the hopes of acquiring a product (Turel *et al*., 2011). Given that competition intensity can be high in some auctions and that things typically become more intense as the auction nears completion, the longer an individual remains engaged in the bidding process the more likely it is that s/he will experience strong emotions (Adam *et al*., 2011). Those who experience auction fever may find that they have little control over their bidding and buying behaviour, ultimately spending more than they anticipated and experiencing negative feelings such as regret as a result.

Thus, whether bidding behaviour is seen as rational or irrational, and whether overpayment is real (in an objective sense relative to a reference price that represents an item's actual worth) or not the subjective emotional assessment of having overpaid for an item is a problem that is relevant for both research and practice, as winner's regret can cause customer dissatisfaction (Amyx & Luehlfing, 2006). Customers who are dissatisfied with their online auction experience are less likely to return to the auction site, and this can be damaging to online auction service providers. Unfortunately, little is known about the factors that lead to winner's regret, defined here as regret associated with the subjective emotional assessment of having overpaid for an item (regardless of whether the amount paid actually exceeds what the item is objectively worth).

Park *et al*. (2012) investigated how key escalation drivers (e.g. completion effect, self-justification and sunk cost) affect an individual's willingness to continue bidding, which in turn leads to overbidding behaviour (i.e. bidding in excess of one's reservation price regardless of whether or not one wins the auction). Their study dealt with overbidding behaviour and did not consider examine winner's regret *per se*. Moreover, they did not examine any emotional triggers that might be associated with this phenomenon. In this paper, we explore the problem of winner's regret using the automatic thinking perspective as a meta-theoretical lens.

Automatic thinking

Automatic thinking is one of two information processing approaches that guide human perception, memory, decision and attention. Automatic thinking involves rapid and parallel processing and requires little effort. Schneider & Shiffrin (1977) distinguish automatic thinking from reflective thinking, which is much slower. Automatic thinking does not require higher-order mental operations, which include executive functions such as making deliberate judgments and evaluations (Strack & Deutsch, 2004). In other words, automatic thinking tends to be involuntary and requires no attention, whereas reflective thinking is voluntary and requires attention. Moors & De Houwer (2006) also reviewed the characteristics that distinguish automatic thinking from reflective thinking, concluding that one of the most important distinctions between the two is the degree to which actions are subject to conscious control. When peoples' activities are automatic, they tend to be more likely to occur autonomously, i.e. they appear to occur on their own in the absence of central control. A third characteristic of automatic thinking is its inherent attentional efficiency. Generally speaking, activities associated with automatic thinking occur with a minimum of attentional capacity, which leaves more capacity for the performance of other tasks. Finally, automatic thinking can be quite difficult to stop or modify, because it involves relatively little in the way of conscious monitoring.

In the context of online auctions, automatic thinking may explain why individuals are prone to overpayment (either real or perceived) and to experience regret as a result. Ariely & Simonson (2003) demonstrated previously that overpayment in online auctions can be conceptualised as a form of automatic thinking, in which bidders lose their self-control and get caught up in the bidding process. The key features of automatic thinking and how they apply to online auction behaviour are shown in Table 1.

Both cognitive and emotional factors can trigger automatic thinking. While cognitive factors often connote reflective thinking, this need not necessarily be the case. In other words, there may be aspects of cognition that remain somewhat opaque to reflective processes or that occur with such frequency that they become automatic over time. An example of the latter would be when driving a car and we come to a red light, we automatically know to stop and we engage the brake on the automobile. Clearly, there is cognition taking place in this action, but it is not something that we consciously think about unless we are a new driver. This example illustrates how something that at one time required reflection can become automatic with sufficient practice. There

Table 1. Applications of automatic thinking processes to online bidding behaviour

Automatic decision process	Application of the automatic process to online bidding behaviour
Unreflective	Bidders may not control their bidding behaviour during the bidding stage.
Effortless	Bidders tend to automatically make bids without making the effort to compare auction price against retail price.
Fast	Bidders tend to make decisions more quickly.

Source: Adapted based on Thaler & Sunstein (2009) applied to our study context.

are also instances in which cognitive factors influence our decision-making without our being fully aware of their impact. One example of this is sunk cost. Arkes & Blumer (1985) showed that when individuals invest in season tickets, they attend more shows. Presumably, this is because they have incurred sunk cost in buying the season tickets. However, if you were to ask these individuals why they chose to attend more shows, they might not even be aware that sunk cost was a factor influencing their attendance decisions. In this sense, sunk cost can be viewed as a cognitive factor that may operate at a subconscious level, resulting in automatic thinking. While sunk cost should not influence decisions from a rational economic perspective, numerous studies (e.g. Arkes & Blumer, 1985) have found that individuals find it difficult to ignore sunk cost when they make decisions. Moreover, the concept of sunk cost is not limited to financial investments but also extends to investments of time and effort. Consistent with prospect theory, the effect of sunk cost on decision-making is believed to arise from the manner in which decisions are framed (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). Specifically, prior research has shown that individuals are more risk-seeking when decisions are framed as a choice between losses, and sunk cost can induce such a framing. Essentially, sunk costs evoke a loss framing, and this triggers risk-seeking behaviour in accordance with prospect theory. In the online auction context, ‘previous bids and/or time invested in the auction represent sunk costs’ (Ku *et al*., 2005, p. 92). Consistent with Park *et al*. (2012), we posit that individuals perceive sunk costs as losses that can only be recouped if the individual wins the auction.

It is also possible that sunk cost (in the form of time and effort) may lead to the endowment effect, which refers to the fact that people tend to ascribe more value to things merely because they own them. Research on the endowment effect has shown that owners often value an item at more than twice the level that an average buyer is willing to pay (Thaler, 1980; Kahneman *et al*., 1990). Carmon & Ariely (2000) suggest that this disparity can be interpreted as form of loss aversion on the part of owners. Specifically, when one owns an item, giving it up is viewed as a loss, and it is well known that individuals exhibit loss aversion (Carmon & Ariely, 2000; Looney & Hardin, 2009; Hardin & Looney, 2012). In an online auction context, sunk costs associated with the bidding process may cause bidders to become so attached to what they are bidding on they begin to develop a sense of ownership over the item. If this occurs, the endowment effect may result in bidders’ overestimating the value of the item just as owners tend to overvalue their possessions. Indeed, prior research on online auctions has offered some empirical support for product attachment as a cause of overpayment (e.g. Carmon & Ariely, 2000; Ariely & Simonson, 2003). At some point, the idea of ‘losing’ the item by not winning the auction creates behaviour that is consistent with loss aversion. Loss aversion can be explained by the value function of prospect theory and the fact that individuals weigh losses roughly two and a half times greater than equivalent gains (Looney & Hardin, 2009).

In sum, sunk costs (in the form of time and effort) may produce a loss framing or create an endowment effect that leads to loss aversion, either of which could theoretically result in bidding behaviour that can result in winner’s regret. Regardless of the exact mechanism through which sunk cost influences bidding behaviour, we suggest that it serves as cognitive trigger for automatic thinking in the online auction context and that it may lead to winner’s regret.

In addition to cognitive factors, emotional factors can also trigger automatic thinking. Prior research suggests that people often make snap decisions based on their emotional state (Ariely &

Simonson, 2003; Amyx & Luehlfing, 2006). Thus, emotions can influence an individual's decision-making without the individual even being aware of the impact. For example, the angrier one feels, 'the more one perceives others as responsible for a negative event' (Lerner & Tiedens, 2006, p. 118). Indeed, numerous studies have demonstrated that strong emotions can have a significant influence on decision-making behaviour (see, for example, Andrade & Ariely, 2009).

In this research, we posit that emotional as well as cognitive factors can influence online bidding behaviour. One emotional factor that can trigger automatic thinking in the online auction context is trait impulsiveness. Trait impulsiveness involves a tendency to act on a whim, displaying behaviour characterised by little or no forethought, reflection or consideration of consequences (VandenBos, 2007). Trait impulsiveness has been linked to automatic thinking (Hofmann *et al.*, 2009), and in the marketing literature, it has been shown to influence buying behaviour (Rook, 1987; Rook & Fisher, 1995). Individuals who are impulsive are more likely to acquire products when presented with the opportunity (Rook & Fisher, 1995). Presumably, this is because trait impulsiveness promotes automatic thinking, causing individuals to make decisions without consciously weighing costs and benefits. An example of such impulsiveness is when an individual enters a supermarket with a list of groceries to buy and encounters a display case of candy bars in a prominently placed location near the checkout. Without necessarily weighing the costs and benefits associated with the purchase, individuals may be inclined to make an impulse purchase and buy themselves a treat that they had not intended to buy. When this occurs, it is often because the individual has an emotional reaction to seeing the product. In this sense, impulsiveness can be viewed as an emotional factor that operates at a subconscious level, resulting in automatic thinking. In this research, we investigate trait impulsiveness as an emotional trigger for automatic thinking in the online auction context, which may lead to winner's regret. While the impact of trait impulsiveness has not been explored in the online auction context, prior research does suggest that emotional factors (e.g. competitive arousal) can play a role in bidding behaviour (Ku *et al.*, 2005).

Although prior research has suggested that both cognitive and emotional factors may affect online bidding behaviour, the combined effect of these two types of factors has not been examined within the confines of a single study. Table 2 provides a representative list of 11 studies that have sought to identify cognitive *or* emotional factors that affect online auction outcomes. The list is not intended to be exhaustive, but it contains the major studies that have been published in this area, and we believe it is representative of online auction studies that have focused particular attention on bidding behaviour. As shown in Table 2, the studies that have been conducted to date invariably focus on *either* the cognitive aspects of why bidders decide to make bids or the emotional aspects that drive bidding behaviour. In order to better understand bidding behaviour in online auctions, however, we believe that it is important to consider *both* cognitive *and* emotional factors in researching this phenomenon, and this is the approach taken here.

RESEARCH MODEL AND HYPOTHESES

Drawing on the meta-theoretical perspective of automatic thinking, we explore sunk cost as a cognitive trigger and trait impulsiveness as an emotional trigger that can lead to winner's regret. Figure 1 illustrates our proposed research model. As shown in the model, both sunk cost and

Table 2. Previous studies on bidder's behaviours (chronological order)

Focus	Bidding behaviour from emotional or cognitive perspective	Variables		
Authors		Independent variable(s)	Dependent variable(s)	Key contribution
Wilcox (2000)	Cognitive	Past auction experience	Likelihood of a bidder bidding in the final moments of an auction	More experienced bidders are more likely to bid according to theoretical predictions
Dholakia *et al*. (2002)	Emotional	Auction attributes (volume of available listings, and posted reservation price) and agent attributes (buyer and seller experience)	Likelihood of herding bias	Examined herding bias in the psychological processes of bidders in online auctions
Oh (2002)	Emotional	Product value, retail price dispersion and auction type	Winner's curse	Examined the differences between C2C and B2C auctions by comparing the likelihood and magnitude of the winner's curse
Stafford & Stern (2002)	Cognitive	Affinity with the computer, intention to use, ease of use, perceived usefulness and involvement	Bid/did not bid	Examined consumer bidding behaviour on online auction sites by illuminating three different theories such as technology acceptance model, the affinity theory and the involvement theory
Gilkeson & Reynolds (2003)	Cognitive	Opening price, number of unexpected bids, bidder experience, seller reputation and auction length	Auction success and final closing price	Investigated how the characteristics of online auctions impact outcomes such as auction success and final closing price
Bapna *et al*. (2004)	Cognitive	Time of entry, time of exit and number of bids	Bidding strategy properties	Identified heterogeneous bidder strategies and the implications for auction design
Wally & Fortin (2005)	Cognitive	Reserve price value, research price disclosure and bidding history	Auction interests	Found that reserve price, reserve disclosure and the initial bidding process had

(Continues)

Table 2. (Continued)

Focus	Bidding behaviour from emotional or cognitive perspective	Variables		
Authors		Independent variable(s)	Dependent variable(s)	Key contribution
				significant effects on a bidder's decision-making process. A combination of these three factors influences a bidder's auction interest
Peters & Bodkin (2007)	Emotional	Compulsive consumption, compulsive gambling and internet addiction	Problematic online auction behaviours	Explored bidders' behaviour that could lead to an online auction addiction
Angst *et al.* (2008)	Emotional	Trait competitiveness, impulse buying, hedonic need and strategic exit (mediator)	Price	Investigated the effects of impulsive-buying tendencies, trait competitiveness and hedonic need fulfilment of strategic exit, and moderating role that hedonic need fulfilment on the relationship between impulse-buying tendencies and strategic exit
Park *et al.* (2012)	Cognitive	Completion effect, self-justification, sunk cost and willingness to continue bidding (as a mediator)	Overbidding behaviour	Examined overbidding behaviour, defined as making a bid that exceeded one's reservation price, by drawing on escalation theory

impulsiveness are posited to have direct effects on winner's regret. Both of these relationships, however, are posited to be moderated by competition intensity, which serves as a situational moderator.

Trait impulsiveness is the tendency to act on a whim, with little or no planning or reflection. This construct has been studied extensively by both marketing researchers and clinical psychologists. For example, in the marketing area, Rook & Fisher (1995, p. 306) conceptualised impulsiveness as a consumer trait and defined it as the tendency to buy 'spontaneously, unreflectively, immediately, and kinetically'. In the context of retail shopping, individuals who rated higher on trait impulsiveness have been found to be more likely to experience powerful and persistent urges to buy something immediately and to act on these urges (Beatty & Ferrell, 1997). Marketing researchers agree that impulsive buying involves an instant-gratification component (Rook & Fisher, 1995; Hausman, 2000) and that such behaviour occurs in the spur of the moment (Angst *et al*., 2008). Just as trait impulsiveness can influence purchase behaviour in retail settings, we believe that it can influence behaviour in an online auction context. Specifically, we posit that impulsive individuals will be more likely to repeatedly engage in 'spur of the moment' bidding decisions, making them more likely to bid past their reservation price without really thinking about the consequences of their behaviour.

Further, evidence from clinical psychology research suggests that trait impulsiveness is associated with an inability to suppress emotional urges. For example, Doran *et al*. (2004) examined that the influence of trait impulsiveness on the smokers' ability to maintain abstinence following a 1 day smoking cessation workshop. They found that higher levels of trait impulsiveness were predictive of a more rapid return to smoking following 48 h of nicotine abstinence. In line with this, Mitchell (1999) also found that smokers with high trait impulsiveness have greater difficulty inhibiting smoking than other smokers.

Based on the preceding text, it appears that individuals with high trait impulsiveness have difficulty inhibiting their emotional urges and are thus more likely to experience 'auction fever'. In other words, individuals who are impulsive are more likely to get emotionally caught up in the dynamics of the bidding process. Thus, we suspect that individuals who have high trait impulsiveness are more likely to continue bidding without careful consideration of whether their bid

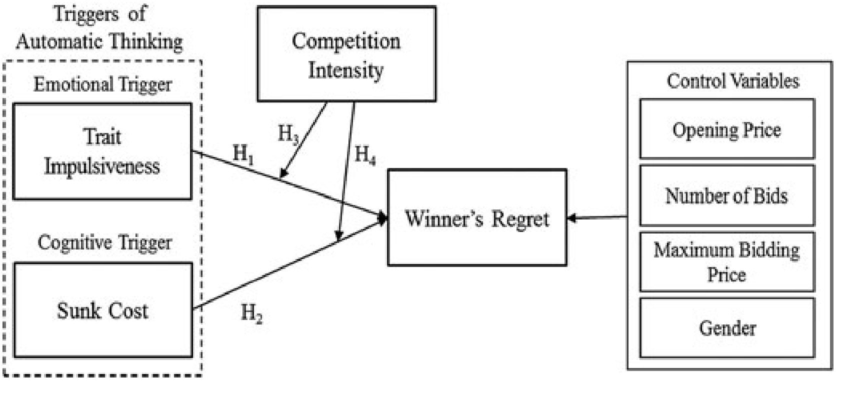

Figure 1. Research model.

exceeds their reservation price, ultimately leading to a greater likelihood of experiencing winner's regret. Based on the preceding text, we hypothesise the following:

H1: Trait impulsiveness will be positively related to winner's regret.

The sunk cost effect, which has been explained from a prospect theory perspective (Whyte, 1986), occurs when an individual's decision-making is influenced by prior investments of time, effort or money that are not recoverable. In the online auction context, 'previous bids and/or time invested in the auction represent sunk costs' (Ku *et al*., 2005, p. 92). As the auction progresses, individuals will tend to perceive sunk cost to be greater as their investment of time and effort becomes higher. Consistent with Park *et al*. (2012), we posit that sunk costs are perceived as losses that can only be recouped if the individual continues to participate in the auction. Thus, in an illusory attempt to recover their sunk cost, individuals may actually bid beyond their reservation price, ultimately leading to winner's regret should they win the auction. As noted earlier, it is also possible that sunk cost (in the form of time and effort) may lead to the endowment effect and that this results in overestimation of value, leading to overbidding and subsequently winner's regret. Both theoretical mechanisms suggest the following hypothesis:

H2: Sunk cost will be positively related to winner's regret.

In the online auction context, individuals are faced with the need to make rapid decisions and are often unable to reflect and conduct research that would guide their bidding behaviour. As a result, people often imitate others (Bonabeau, 2004). Such imitative behaviour can lead to the formation of informational cascades (Bikhchandani *et al*., 1992). Informational cascades occur when individuals follow the previous behaviour of others and disregard their own information. Previous studies on informational cascades have highlighted the importance of social influence in decision-making. On the basis of prior research (Gilkeson & Reynolds, 2003; Johns & Zaichkowsky, 2003; Ku *et al*., 2005), it is reasonable to assume that decision dynamics can be impacted by competition intensity. Park *et al*. (2012) found that the strength of the relationship between bidders' willingness to continue bidding and overbidding behaviour was greater when competition intensity was higher.

Ariely & Simonson (2003) suggest that most auction participants perceive other bidders as 'competitors' and associate auction outcomes with 'winning' and 'losing'. Ku *et al*. (2005) suggest that competition intensity produces 'competitive arousal', an emotional state that causes individuals to shift from a motivation to acquire a product for a reasonable price to a motivation to win the auction at any cost (Ku *et al*., 2005). Their competitive arousal model places special emphasis on two antecedents of competitive arousal: heightened perceptions of rivalry and increasing time pressure (which characteristically occurs as an auction nears completion). Based on the preceding text, we expect there to be an interaction between competition intensity and trait impulsiveness such that a more intense competitive environment can stimulate those with high trait impulsiveness to be even more likely to bid past their reservation price, thus increasing the chances that they will experience winner's regret. Thus, we offer the following hypothesis:

H3: The strength of the relationship between impulsiveness and winner's regret will be greater when competition intensity is high.

In the online auction context, bidders invest their time and effort. These investments represent sunk costs and can only be recovered if the auction is eventually won. Ku *et al*. (2005) reported that high sunk costs lead to increased self-reported levels of arousal and higher bidding activity. They argued that if bidding itself is arousing, this can 'feed a vicious cycle of bidding'. In line with this, Park *et al*. (2012) found that auction participants' willingness to continue to bidding is influenced by sunk cost. Interestingly, their results also suggest that competition intensity moderates the relationship between sunk cost and willingness to continue bidding, such that the effect of sunk cost is weakened under conditions of high competition intensity. They also reported that sunk cost had a direct effect on overbidding when competition intensity was low, but not when competition intensity was high. Together, these results indicate that competition intensity can play an important moderating role in this context, weakening the effect of sunk cost.

Moon (2001) suggests that the effect of sunk cost differs depending on whether an individual is focused on the past or the future, and this provides a possible theoretical explanation as to why the sunk cost effect may be weakened when competition intensity is high. Specifically, the effect of sunk cost is theorised to be less potent when an individual is thinking about the future as opposed to the past. As Moon (2001) suggests, sunk cost causes decision-makers to think about the past, which leads them to try and recover monies already spent by continuing a previously chosen course of action. However, as competition intensity increases, we theorise that individuals become more absorbed in the auction dynamics and begin to envision a future state in which the auction is over and they also begin to realise that they may or may not win the auction.

Moreover, as competition intensity increases, individuals are more likely to experience the effects of competitive arousal, which is an adrenaline-laden emotional state that can arise during highly competitive bidding (Ku *et al*., 2005). According to the competitive arousal model of Ku *et al.* (2005), there are two key antecedents of competitive arousal: heightened rivalry and increasing time pressure. These conditions can create an environment in which the desire to win the auction becomes so strong that it can lead to dysfunctional behaviour (Malhotra, 2010). We propose that when competition intensity is high, the combined effects of heightened rivalry and time pressure are likely to overshadow any effects of previous investments in time and effort (i.e. sunk cost). If competition intensity is high enough, competitive arousal could even create an environment in which bidders are willing to pay more than item is worth just to deprive other bidders from obtaining the item. If this occurs, the gratification that comes from winning the auction at any cost may diminish the negative feelings that would normally be associated with winner's regret. Thus, the relationship between sunk cost and winner's regret may be weakened under conditions of high competition intensity.

Thus, we expect that high competition intensity causes individuals not to think about the past but rather to focus on the future, and can even lead to situations where there is gratification associated with depriving others from winning the auction, thereby weakening the effect of sunk cost on winner's regret. Therefore, we expect that under conditions of high competition intensity, the effect of sunk cost on bidding behaviour is weakened and the predictive value of sunk cost on winner's regret is reduced. Based on this logic, we advance the following hypothesis:

H4: The strength of the relationship between sunk cost and winner's regret will be greater when competition intensity is low.

METHODOLOGY

Research approach and construct operationalisation

We employed a survey approach in order to test our research model (see Appendix A for our measures, which were all based on self-reports). Impulsiveness was operationalised using a four-item scale (IMP1–IMP4) adapted and modified from Rook & Fisher (1995), which was designed to assess the extent to which an individual acts spontaneously without thinking of the consequences. Sunk cost was operationalised using a three-item scale (SC1–SC3) adapted from Park *et al*. (2012), which captured the extent to which the bidder perceived that it would be difficult to stop bidding due to prior investment of time or effort in the auction process. Competition intensity was operationalised using a three-item scale from Park *et al*. (2012). These measures were designed to tap into the number of people competing in the auction and how fierce the competition was perceived to be (CI1–CI3).

Our dependent variable, winner's regret, was assessed using a single-item measure designed to capture regret associated with the subjective emotional assessment of having overpaid for an item. Single-item scales are frequently seen as being less reliable than multi-item scales, but 'as far as internal consistency reliability is concerned, there is substantial evidence indicating acceptable reliability values for single-item scales' (Fuchs & Diamantopoulos, 2009, p. 201). Single-item scales also tend to raise concerns regarding the assessment of convergent and discriminant validity, but again, the available evidence suggests that 'single-item measures can be both reliable and valid' (Wanous *et al*., 1997; Robins *et al*., 2001; Wanous & Hudy, 2001; Fuchs & Diamantopoulos, 2009, p. 203).

The issue of whether or not to use a single-item measure depends on a variety of factors, but the nature of the construct is certainly an important consideration (Fuchs & Diamantopoulos, 2009; Petrescu, 2013). Petrescu (2013) notes that single-item measures can be used to assess concepts that are simple and easy to understand. This includes not only concrete concepts, such as sales or expenditures, but also behavioural constructs, such as repeat purchase intention. Fuchs & Diamantopoulos (2009) suggest that it is reasonable to employ single-item measures for unidimensional constructs where there is broad agreement as to what the construct means (e.g. favorability, price perception and buying intention). In our case, the winner's regret construct was unidimensional and easy to understand, which made it possible to assess the construct with a single measurement item ('After purchasing the item, I regretted that I had overpaid'). What makes the construct unidimensional is that it can be measured using a single 'ruler' that goes from low to high. While one could argue that the general concept of regret may have multiple dimensions (i.e. perhaps one may regret something for all kinds of different reasons), we are not attempting to capture the general concept of regret. Instead, we are focusing in on and measuring a very specific kind of regret (i.e. regret associated with the subjective emotional assessment of having overpaid for an item). By restricting the concept in this way, we are able to treat it as a unidimensional construct.

In addition to the previous constructs, we controlled for four variables that might influence bidding and perceptions in our research setting: (1) opening price on the focal item, (2) the total number of bids placed on the focal item, (3) maximum bidding price submitted by the bidder and (4) gender.

Instrument validation and data collection

An initial version of the questionnaire was developed with the idea that each subject would be asked to respond based on his or her most recent online auction experience, answering questions about regret after winning an auction. Four bilingual individuals with domain expertise in online auctions and experience with survey design provided feedback that was used to refine the questionnaire. The survey was developed in English and translated into Korean by two individuals who were fluent in both English and Korean. Two other individuals who were also fluent in both English and Korean performed a backward translation to ensure consistency between the Korean version of the measurement items and the original English version. Minor adjustments were then made to eliminate any translation-related differences and to ensure that the meaning was equivalent.

The questionnaire was then pilot tested with 196 undergraduate students, allowing us to check the psychometric properties of the scales (Straub *et al*., 2004). Convergent validity of each scale was assessed using a principal components factor analysis. A separate principal components factor analysis was run for each of the constructs. A single eigenvalue above 1 for each construct verified that the construct was unidimensional, hence, providing evidence of convergent validity for each scale. An exploratory factor analysis with all constructs revealed a clean factor structure and exhibited item-to-construct loadings that exceeded the desired threshold of 0.5. Cronbach's alpha was used to assess the reliability of our measures in the pilot test, and all scales were judged to exceed the normal threshold of 0.7 for reliability (Hair *et al*., 1998).

Subsequent to the pilot test, we administered a Web-based survey that targeted individuals who had participated in online auctions using one of Korea's leading online auction sites. We contracted with a market research firm, which agreed to administer the survey to Koreans with prior experience using online auctions to acquire goods. Our aim was to obtain a representative sample of auction users that included participants from different age ranges. We instructed the market research firm to obtain 500 responses and to restrict the sample to those who indicated they had some actual experience of buying products in online auctions. Participants were asked to recall an online auction that they had participated in within the last month in which they had actually won the auction and to complete the survey based on that auction experience. Five dollars of cyber-money was provided to each survey recipient as an incentive to complete the survey.

A total of 500 responses were obtained, but some had to be dropped because they were not fully completed, leaving us with 479 completed surveys. Because we were interested in studying winner's regret in online auctions, we restricted our analysis to survey respondents who indicated that they felt regret after purchasing their item. A total of 301 survey respondents met this threshold and these cases were retained for further analysis. Of the 301 usable responses, 70 respondents purchased clothes (23.3%), 88 respondents purchased consumer electronics (e.g. digital camera, MP3 players and used computers) (29.2%) and 143 respondents (47.5%) purchased miscellaneous goods such as watch, shoes and wallets. Our survey respondents reported using the following online auction sites the most – Auction (http://www.auction.co.kr) (82%), G-market (http://www.gmarket.co.kr) (16%) and Onket (http://www.onket.com) (2%) – as these are the most popular online auction sites in Korea.

All survey items for the constructs in our study were measured on a seven-point Likert scale, which ranged from *strongly disagree* (1) to *strongly agree* (7). Our data were analysed using partial least squares and regression using SmartPLS 2.0 (Ringle *et al*., 2005) and the SPSS 18.0, respectively. We used PLS for our analysis as it (1) enabled us to estimate the measurement model and the structural model simultaneously, (2) is suitable for exploratory models and (3) has fewer distributional assumptions (Gefen & Straub, 2005). We chose PLS over covariance-based Structural Equation Modeling (SEM) also because our emphasis is on prediction rather than model fit.

DATA ANALYSIS AND RESULTS

Descriptive analysis

Table 3 shows the demographic profile of our respondents. 67.4% of our respondents were male and 32.6% were female. Most respondents (75.1%) were in the 21–40 years age group. Most respondents (46.2%) placed bids between one and three times and 27.2% of total respondents placed bids between four and six times.

We employed two methods to test for common method bias (CMB) as it represents a potential threat to validity given our study design. First, we used Harman's one-factor test (Podsakoff & Organ, 1986). According to Podsakoff & Organ (1986), if a single factor emerges from the factor analysis, this may be indicative of a serious CMB threat. In order to conduct this test, we entered all 11 measurement items into a principal component analysis and examined the results of the unrotated factor solution. Four factors were extracted, accounting for 26.39%, 24.38%, 24.21% and 8.90% of the variance, respectively. This result suggests that CMB was not a significant threat in our study.

Second, we conducted marker variable analysis per Lindell & Whitney (2001) in which unrelated constructs (termed marker variables) are used to adjust the correlations among the principle constructs. We identified two unrelated constructs (opening price and perceived ease of use), which were assessed as part of the survey. High correlations among any of the items of the study's principal constructs and unrelated constructs would indicate common method bias as the constructs of opening price and perceived ease of use should be weakly related to the study's principle constructs. The results of our marker variable analysis (described in Appendix F) suggest that common method bias was likely not a significant threat in this study.

Measurement model

For the measurement model, each construct was modelled reflectively. The measurement model was tested by examining convergent and discriminant validity (Fornell & Larcker,

Table 3. Sample demographics

Items	Category	Frequency	Percentage (%)
Gender	Men	203	67.40
	Women	98	32.60
Age (years)	10–19	8	2.70
	20–29	92	30.60
	30–39	134	44.50
	40–49	57	18.90
	Over 50	10	3.30
Number of Bids for a Product	1–3	139	46.20
	4–6	82	27.20
	7–10	31	10.30
	11–15	24	8.00
	Over 16	25	8.30
Number of visits to online auction site (monthly)	1–3	136	45.2
	4–6	116	38.5
	7–10	32	10.6
	11–15	15	4.0
	Over 16	5	1.7

1981). Two different assessments were made for convergent validity: (1) individual item reliability and (2) construct reliability. Individual item reliability was assessed by examining the item-to-construct loadings for each construct that was measured with multiple indicators. In order for the shared variance between each item and its associated construct to exceed the error variance, the standardised loadings should be greater than 0.70. As can be seen in Appendix B, all of our item to-construct loadings exceeded the desired threshold.

The next step in establishing measurement reliability was to examine the internal consistency for each block of measures (i.e. construct reliability). This was performed by examining the composite reliability, Cronbach's alpha and the average variance extracted (AVE) for each block of measures, as shown in Table 4. Composite reliability and Cronbach's alpha both measure the internal consistency within a given construct's items. The threshold values for composite reliability and Cronbach's alpha are not absolute ones, but our measures appear to be more than acceptable by established criteria. Bearden *et al*. (1993) claim that a score of 0.7 indicates 'extensive' evidence of reliability and a score of 0.8 or higher provide 'exemplary' evidence. As shown in Table 4, all of the constructs in our measurement model exhibited composite reliabilities of 0.86 or higher, and they all exhibited Cronbach's alpha of 0.80 or higher.

The guideline threshold for AVE is 0.5, meaning that 50% or more variance of the indicators is accounted for Chin (1998). As Appendix C indicates, all of the constructs in our measurement model exceeded the established criteria for AVE.

We conducted two tests for discriminant validity. First, we calculated each indicator's loading on its own construct as well as its cross-loading on all other constructs (Appendix B). The loadings for the indicators for each construct are higher than the cross-loadings for other constructs' indicators. Additionally, going across the rows, each indicator has a higher loading with its construct than a cross-loading with any other construct. This provides good evidence of discriminant validity (Chin, 1998, p. 321).

As a second test of discriminant validity, we considered whether the square roots of the AVEs of the latent constructs were greater than the correlations among the latent constructs. When this is true, more variance is shared between the latent construct and its block of indicators than with another construct (Chin, 1998). As can be seen by reading across the rows of Appendix C, our measures passed this test, thus providing additional evidence of discriminant validity.

Hypotheses testing

The explanatory power of a structural model can be evaluated by looking at the R^2 value (variance accounted for) of the final dependent construct. The final dependent construct in this study (winner's regret) has an R^2 value of 0.229, indicating that the model accounts for 22.9% of the variance in the dependent variable.

As shown in Figure 2, the path between impulsiveness and winner's regret ($\beta = 0.276$, $t = 3.846$) and the path between sunk cost and winner's regret ($\beta = 0.266$, $t = 3.628$) were both significant at $p < 0.01$. These results provide strong support for H1 and H2. None of the control variables were found to be significant. While some have suggested that gender differences do exist when it comes to regret, we may not have observed this because of the fact that there were far fewer females than males in our study.

Moderating effects of competition intensity

In order to test the moderating effect of competition intensity (H3–H4) on the relationship between our two independent variables (trait impulsiveness and sunk cost) and our

Table 4. Descriptive statistics and reliability of constructs

Total sample group ($n = 301$)	Mean	SD	Cronbach's alpha	Composite reliability	AVE
Competition intensity	4.60	1.17	0.92	0.95	0.87
Trait impulsiveness	4.21	1.22	0.86	0.91	0.71
Winner's regret	3.96	1.25	—	—	—
Sunk cost	4.35	1.30	0.96	0.97	0.92
High competition intensity group ($n = 155$)	Mean	SD	Cronbach's alpha	Composite reliability	AVE
Trait impulsiveness	4.43	1.29	0.89	0.92	0.75
Winner's regret	4.23	1.38	—	—	—
Sunk cost	4.93	1.16	0.94	0.96	0.89
Low competition intensity group ($n = 146$)	Mean	SD	Cronbach's alpha	Composite reliability	AVE
Trait impulsiveness	3.98	1.05	0.80	0.86	0.61
Winner's regret	3.66	1.03	—	—	—
Sunk cost	3.73	1.15	0.95	0.97	0.91

SD, standard deviation.

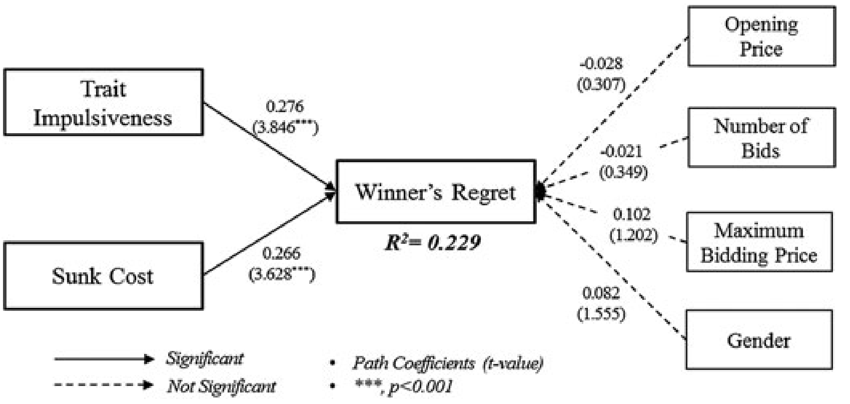

Figure 2. Path analysis.

dependent variable (winner's regret), we performed a subgroup analysis as explained in the succeeding text. Before embarking on a subgroup analysis for competition intensity (CI), we first needed to determine whether CI acts as a moderator, and if so, what type of moderator it is.

In order to investigate the moderating role of CI on the relationship between our two predictors (trait impulsiveness and sunk cost) and our criterion variable (winner's regret), we followed the moderated regression analysis (MRA) procedure recommended by Sharma *et al*. (1981). Using MRA, one can determine the type of moderator based on a few simple rules. If there is an interaction effect and no direct effect with criterion or predictor variables, we can conclude that the variable is a pure moderator. If there is an interaction effect and a direct relationship with the predictor, the criterion variable or both, we can conclude that the variable is a quasi-moderator. If there is neither a direct effect nor a moderation effect but the detected interaction derives from unequal measurement errors across subsamples, we can conclude that the variable is a homologiser.

Based on the MRA procedure, and applying a strict $p < 0.05$ significance threshold, we concluded that CI was a moderator, but that it is neither a pure moderator, nor a quasi-moderator. Instead, CI acts as a homologiser (Appendix D). A homologiser Z acts as moderator in that it influences the strength of the relationship between X (an independent variable) and Y (a dependent variable) but is not itself related to X or Y and does not interact with X. Under such circumstances, Z exerts its influence through the error term, and the appropriate way of analysing the moderating effect of Z is by partitioning the dataset and performing a subgroup analysis (Sharma *et al*., 1981; Allison *et al*., 1992). In order to do this, we split the sample into high competition intensity and low competition intensity subgroups. This was performed by splitting the sample at the mean value of CI (4.60), after which, we also tested both reliability and validity for each subgroup. Appendix B and Appendix C show that all items in the CI subgroup ($n = 155$) demonstrate acceptable loadings (0.788–0.950), as do all items in the low-CI subgroup ($n = 146$) (0.779–0.969). In addition, the reliability indicators are all well above accepted thresholds, and the AVEs are greater than 0.5.

Following Carte & Russell's (2003) suggestion, we assessed whether the latent constructs were perceived in a similar fashion between the high-CI and low-CI subgroups. An examination of Appendix B suggests that the loading patterns are very similar, thus suggesting that meaningful comparisons can be made between groups. In addition, a measurement invariance analysis was performed to further validate the similarity of measurement models between the two subgroups (Cheung & Rensvold, 2002). Appendix E provides support for measurement invariance, and on that basis, we concluded that meaningful path coefficient comparisons could be made across subgroups. With the measurement model appearing to be stable and adequate across the subgroups, we proceeded to analyse the structural model for each subgroup.

Consistent with the Sharma *et al*. (1981) approach for analysing a homologiser, we tested the moderating effect of competition intensity by estimating two separate models in PLS, namely, the high-CI subgroup and the low-CI subgroup. This approach allowed us to examine the moderating effect of CI by looking at the differences in the magnitude of the path coefficient from impulsiveness to winner's regret across groups using the approach suggested by Chin *et al*. (2003). This involved computing a *t*-statistic[2] as follows:

$$S_{pooled} = \sqrt{\left\{[(N-1)/(N_1+N_2-2)]\times[(N_2-1)/N_1+N_2-2]\times SE_2^2\right\}}$$
$$t = (PC_1 - PC_2)/\left[S_{pooled}\times\sqrt{(1/N_1)+(1/N_2)}\right]$$

As shown in Table 5, comparison of the path coefficient from impulsiveness to winner's regret is larger for the high-CI subgroup ($\beta = 0.313$) than for the low-CI subgroup ($\beta = 0.184$), whereas the path coefficient from sunk cost to winner's regret is larger for the low-CI subgroup ($\beta = 0.337$) than for the high-CI subgroup ($\beta = 0.168$).

In other words, trait impulsiveness has a greater impact on winner's regret when the level of competition is high, thus supporting H3, whereas sunk cost has a greater impact on winner's regret when competition intensity is low, thus supporting H4. These findings indicate that the impact of trait impulsiveness as well as sunk cost on winner's regret differs depending on the level of competition intensity. As indicated in Table 6, all of our hypotheses were supported.

CONCLUSIONS AND IMPLICATIONS

In this study, we applied the automatic thinking perspective as a meta-theoretic lens to explain why online auction bidders succumb to both trait impulsiveness and sunk cost, ultimately leading them to experience winner's regret. This perspective allowed us to generate insights into one possible mechanism underlying winner's regret, by focusing our attention on both a cognitive trigger (i.e. sunk cost) and an emotional trigger (i.e. trait impulsiveness) of automatic thinking. To add further richness to our research model, we also considered a situational moderator (i.e. competition intensity). Our results show that both impulsiveness and sunk cost can promote winner's regret and that the

[2]where, S_{pooled}: the pooled estimator of the variance; PC_i: path coefficient in structural model of competition intensity group *i*; N_j: sample size of dataset for competition intensity *i*; SE_i: standard error of path in structural model of competition intensity *i*; and t_{ij}: *t*-statistic with $N_1 + N_2 - 2$ degrees of freedom.

Table 5. Comparisons of paths in each group (competition intensity)

From ➔ to	High CI (n = 155)		Low CI (146)			
	Path coefficient	SE	Path coefficient	SE	R^2	t-statistic
Trait impulsiveness ➔ winner's regret	0.313	0.101	0.184	0.098	0.168	11.235
Sunk cost ➔ winner's regret	0.168	0.102	0.337	0.077	0.196	16.149

SE, standard error.

Table 6. Summary of hypotheses testing results

#	Hypotheses	Results
1	Trait impulsiveness will be positively related to winner's regret.	Supported
2	Sunk cost will be positively related to winner's regret.	Supported
3	The strength of relationship between trait impulsiveness and winner's regret will be greater when competition intensity is high.	Supported
4	The strength of relationship between sunk cost and winner's regret will be greater when competition intensity is low.	Supported

relationship between these triggers and winner's regret is moderated by competition intensity. Specifically, we found that competition intensity strengthens the relationship between impulsiveness and winner's regret, but that it weakens the relationship between sunk cost and winner's regret. Before turning to the implications of our study, it is appropriate to consider its limitations.

First, we relied on a survey-based approach and did not collect actual bidding data. This means that our measures are subjective and open to potential recall bias. To minimise the risk of recall bias, we asked participants to recall an online auction that they had participated in within the last month and to complete the survey based on that auction experience. One benefit of our approach is that we were able to gather data in an unobtrusive manner that did not risk interfering with the decision-making of the participants as they engaged in the auction process (Todd & Benbast, 1987).

Second, we used a single-item measure for our dependent variable that cannot be assessed for reliability. Although we suggest that the use of a single-item measure is justified in this context due to the unidimensional nature of our focal construct, future research should be conducted with a multi-item measure that can be assessed for reliability to test the robustness of our findings.

Third, although we employed automatic thinking as a meta-theoretic perspective to guide our research, we did not gather the kinds of physical measurements (e.g. functional Magnetic Resonance Imaging (fMRI)) that would allow us to confirm the proposed mechanism and the brain activity associated with it. Additional research is needed in order to confirm the underlying mechanism posited here and to probe other factors (both cognitive and emotional) that may also promote or impede winner's regret. In spite of the aforementioned limitations, we believe that our work has important implications for both research and practice.

Implications for research and practice

This research makes several important contributions to both research and practice. In this paper, we draw upon the automatic thinking perspective and consider *both* cognitive *and* emotional factors in order to better understand bidding behaviour in online auctions. Specifically, we provide empirical evidence that both trait impulsiveness and sunk cost influence winner's regret. Further, we show that competition intensity has a moderating role on these relationships. Specifically, trait impulsiveness has a greater impact on winner's regret when the level of competition is high, whereas sunk cost has a greater impact on winner's regret when competition intensity is low. These findings indicate that the impact of trait impulsiveness as well as sunk cost on winner's regret differs depending on the level of competition intensity.

Our findings also have practical implications for online auction participants as well as auction site operators. From the perspective of both online auction participants as well as online auction providers, it is important to know that there can be negative repercussions (i.e. winner's regret) that result from both the time and the energy that an individual invests in an auction as well as the degree of impulsiveness that an individual brings to the auction. For online auction participants, minimising winner's regret requires getting in the habit of honouring one's initial reservation price and resisting the temptation to obsessively check the status of the auction and to incrementally increase one's bidding limit when one is outbid. Auction participants should be especially wary about falling into a trap that will lead to winner's regret when competition intensity is high. Under these conditions, participants need to be very careful not to succumb to their own impulsiveness even if it means losing the auction.

For auction site operators, our findings create the possibility of predicting which individuals will be more likely to experience winner's regret. Specifically, auction site users could be given a survey prior to participating in online auctions to determine their trait impulsiveness and susceptibility to the sunk cost effect. The results could be used to gauge how likely it is that individuals will experience winner's regret and auction site users could be warned beforehand. In cases where the risk of winner's regret is high, the auction site could even recommend that individuals use the 'buy it now' feature instead of online bidding.

Our research also provides a tool for online auction sites to survey online auction winners to determine the extent to which they experienced winner's regret. This can be an informative diagnostic tool for helping auction sites to gauge whether winner's regret is experienced by a handful of users or whether it is something that is experienced more broadly. Once this is known, site management can determine whether any corrective action is needed.

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Biographies

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APPENDIX A. MEASUREMENT ITEMS FOR KEY CONSTRUCTS

Constructs	No.	Measures	Sources
Impulsiveness	IMP1	I usually do things on impulse.	Rook & Fisher (1995)
	IMP2	I often behave without thinking of the consequences.	
	IMP3	I often say the first thing I think.	
	IMP4	I often act on the spur of the moment.	
Sunk cost	SC1	I could not stop bidding because I had already spent too much effort in the process.	Ku *et al*. (2005), Park *et al*. (2012)
	SC2	I could not stop bidding because I had already spent too much time in the process.	
	SC3	Overall, it would have been a waste of time and effort if I stopped bidding.	
Winner's regret	WR	After purchasing the item, I regretted that I had overpaid.	Developed for this study
Competition intensity	CI1	The bidding competition was fierce.	Park *et al*. (2012)
	CI2	There were many people who participated in the bidding process.	
	CI3	Compared with other auctions, there were many bidders who competed in the auction.	

Strongly disagree/*agree* (1–7 scale).
IMP, impulsiveness; WR, winner's regret; SC, sunk cost.

APPENDIX B. ITEM-FACTOR LOADINGS AND CROSS-LOADINGS FOR FULL SAMPLE AND FOR SUBGROUPS

	Full sample (n = 301)					
	Competition intensity	Impulsiveness	Winner's regret	Sunk cost	High CI (n = 155)	Low CI (n = 146)
CI1	0.915	0.241	0.206	0.546	N/A	N/A
CI2	0.944	0.236	0.184	0.507		
CI3	0.933	0.280	0.226	0.583		
IMP 1	0.219	0.850	0.351	0.358	0.883	0.779
IMP 2	0.303	0.800	0.310	0.386	0.788	0.817
IMP 3	0.222	0.848	0.333	0.403	0.890	0.773
IMP 4	0.179	0.868	0.322	0.347	0.899	0.767
WR	0.223	0.391	1.000	0.397	1.000	1.000
SC1	0.589	0.427	0.384	0.966	0.943	0.969
SC2	0.550	0.415	0.381	0.968	0.950	0.970
SC3	0.554	0.432	0.379	0.942	0.930	0.922

N/A, not applicable; IMP, impulsiveness; WR, winner's regret; SC, sunk cost.

APPENDIX C. CONSTRUCT CORRELATIONS AND SQUARE ROOT OF AVES (ON DIAGONAL)

Total sample group ($n = 301$)				
	Competition intensity	Impulsiveness	Winner's regret	Sunk cost
Competition intensity	0.930			
Impulsiveness	0.273	0.842		
Winner's regret	0.223	0.391	0.909	
Sunk cost	0.589	0.443	0.397	0.959
High competition intensity group ($n = 155$)				
	Competition intensity	Impulsiveness	Winner's regret	Sunk cost
Competition intensity	N/A			
Impulsiveness	N/A	0.866		
Winner's regret	N/A	0.389	1.000	
Sunk cost	N/A	0.397	0.294	0.941
Low competition intensity group ($n = 155$)				
	Competition intensity	Impulsiveness	Winner's regret	Sunk cost
Competition intensity	N/A			
Impulsiveness	N/A	0.782		
Winner's regret	N/A	0.339	1	
Sunk cost	N/A	0.397	0.412	0.954

N/A, not applicable.

APPENDIX D. MRA ANALYSIS TO DETERMINE THE TYPE OF MODERATOR FOR COMPETITION INTENSITY

		Unstandardised coefficients		Standardised coefficients			
Model		Beta	Std error	Beta	t	Sig.	R^2
1	Constant	0033.957	0.064		61.665	0.001	0.215
	Impulsiveness (IMP)	0.329	0.071	0.266	4.650	0.000	
	Sunk cost (SC)	0.280	0.057	0.279	4.878	0.000	
2	Constant	3.957	0.064		61.575	0.000	0.215
	Impulsiveness (IMP)	0.330	0.071	0.267	4.648	0.000	
	Sunk cost (SC)	0.293	0.068	0.292	4.294	0.002	
	Competition intensity (CI)	0.073	−0.023		−0.356	0.722	
3	Constant	3.961	0.066		59.686	0.000	0.215
	Impulsiveness (IMP)	0.333	0.072	0.269	4.614	0.000	
	Sunk cost (SC)	0.291	0.069	0.291	4.235	0.000	
	Competition intensity (CI)	−0.024	0.074	−0.021	−0.329	0.742	
	CI*IMP	−0.013	0.054	−0.013	−0.244	0.807	

(Continues)

Table . (Continued)

Model		Unstandardised coefficients Beta	Std error	Standardised coefficients Beta	*t*	Sig.	R^2
4	Constant	4.008	0.071		56.522	0.000	0.223
	Impulsiveness (IMP)	0.336	0.071	0.272	4.748	0.000	
	Sunk cost (SC)	0.290	0.068	0.289	4.257	0.000	
	Competition intensity (CI)	−0.038	0.073	−0.033	−0.52	0.603	
	CI*SC	−0.065	0.038	−0.088	−1.697	0.091	
5	Constant	4.007	0.071		56.413	0.000	0.224
	Impulsiveness (IMP)	0.329	0.072	0.266	4.578	0.000	
	Sunk cost (SC)	0.294	0.069	0.294	4.293	0.000	
	Competition intensity (CI)	−0.045	0.074	−0.039	−0.611	0.542	
	CI*SC	−0.077	0.043	−0.104	−1.784	0.075	
	CI*IMP	0.037	0.061	0.036	0.607	0.544	

Dependent variable: winner's regret.
*$p < 0.001$.

APPENDIX E. MEASUREMENT INVARIANCE ANALYSIS FOR GROUP COMPARISON

Model test	Chi-square	df	Chi-square/df	GFI	CFI	NFI	RMSEA	ΔGFI	ΔCFI	ΔNFI	ΔRMSEA
Fit index											
Baseline model	77.019	48	1.605	0.959	0.985	0.962	0.045	—	—	—	—
Constrained models between											
Model test	Chi-square	df	Chi-square/df	GFI	CFI	NFI	RMSEA	ΔGFI	ΔCFI	ΔNFI	ΔRMSEA
IMP and RGT	77.019	48	1.605	0.959	0.985	0.962	0.045	0.000	0.000	0.000	0.000
SC and RGT	77.019	48	1.605	0.959	0.985	0.962	0.045	0.000	0.000	0.000	0.000
IMP, SC and RGT	77.252	49	1.577	0.959	0.986	0.962	0.044	0.001	0.000	0.001	0.000
IMP, SC, OP and RGT	144.729	50	2.895	0.950	0.976	0.929	0.052	0.009	0.009	0.010	0.009
IMP, SC, OP, NB and RGT	146.093	51	2.865	0.949	0.971	0.928	0.052	0.010	0.001	0.005	0.000
IMP, SC, OP, NB, MP and RGT	149.698	52	2.879	0.945	0.970	0.926	0.052	0.004	0.004	0.003	0.000
IMP, SC, OP, NB, MP, GD and RGT	152.398	53	2.875	0.943	0.969	0.925	0.052	0.002	0.002	0.001	0.000

APPENDIX F. COMMON METHOD BIAS (CMB) ANALYSIS

F1 Marker Variable Analysis to Evaluate Common Method Bias

We followed the marker variable method described by Lindell & Whitney (2001) and used by Malhotra *et al*. (2006). We identified the lowest correlation marker variable collected during survey administration (R_{M1}). We also identified the second lowest correlation marker variable (R_{M2}). In Table , we present the correlations after correcting for R_{M1} and R_{M2}:

- Adjusting for R_{M1} and R_{M2}, respectively, the correlations among the substantive variables dropped by 0.2 in maximum. All significant correlations remained the same significant level and insignificant correlations remained insignificant.

		R_{M1} = 0.008		R_{M2} = 0.009	
Factors	Uncorrected	M1	*t*	M2	*t*
r(IP, SC)	0.444	0.428	8.175	0.426	8.128
r(IP, WR)	0.390	0.374	6.961	0.372	6.918
r(IP,CI)	0.271	0.255	4.552	0.253	4.514
r(SC, CI)	0.585	0.569	11.944	0.567	11.883
r(SC,WR)	0.398	0.382	7.135	0.380	7.092
r(CI, WR)	0.221	0.205	3.616	0.203	3.579

IMP, impulsiveness; SC, sunk cost; CI, competition intensity; WR, winner's regret; M1, opening price; M2, perceived ease of use; R_{M1}, correlation between M1 (marker variable) and WR; R_{M2}, correlation between M2 (marker variable) and WR.

F2 Correlation Tables of Marker Variable and Study Constructs

Constructs	SC	CI	IP	WR	M1	M2
SC	1.000					
CI	0.585	1.000				
IMP	0.444	0.271	1.000			
WR	0.398	0.221	0.390	1.000		
M1	0.012	0.056	−0.145	0.008	1.000	
M2	0.216	0.294	0.205	0.009	0.131	1.000

IMP, impulsiveness; SC, sunk cost; CI, competition intensity; WR, winner's regret; M1, opening price; M2, perceived ease of use.