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Golden eye — How traders focus on and select information in experimental asset markets

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ABSTRACT

In this study, we examine the subjective importance that traders attribute to specific information elements in experimental asset markets in two ways. First, using eye-tracking technology, we determine which given elements garner the most visual focus among traders. Second, we let traders actively choose a limited set of the given elements to determine which ones they deem important to have while trading. Our results indicate that the order book is the most important to traders, while the price chart is of low importance. There is only a conditional alignment between the elements that receive the most visual focus and those that traders select. Additionally, cognitive abilities play a non-trivial role in determining which information elements traders focus on. Finally, we find mixed evidence of a potential link between visual focus and trading performance.

1. Introduction

Over the last decades, global financial markets have become increasingly complex, generating vast amounts of data with which traders are confronted when making their investment decisions. As a consequence, traders must prioritize which of the available information sources they allocate their limited attention to Bose et al. (2022) and Toma et al. (2023). In other words, they need to decide which type of information is more important to them than the others.

Measuring the "importance" of a specific type of information is not straightforward, as it can take at least two distinct forms. One type holds high informational value but requires infrequent consultation, typically because it is static or changes rarely—such as the fundamental value of an asset. The other type may be less critical in absolute terms but benefits from frequent monitoring due to its dynamic nature, such as a price chart. To investigate the subjective importance traders attribute to specific information elements within an asset market context, we adopt two complementary approaches. First, we employ eye-tracking technology to capture visual focus. Second, we allow traders to choose which information elements to access, thereby revealing their importance through their selection behavior.

Eye gaze analysis is a well-established method for measuring attentional focus via visual focus.[1] Computer science, economics, and psychological literature suggest that eye-tracking metrics, such as visual fixations, which we will use to operationalize visual focus, provide clues about cognitive processes (Irwin, 2004; Bednarik et al., 2013), particularly relevant for investigating economic decision-making processes (Fairley et al., 2024; Lohse et al., 2024; Lu et al., 2016). While infrequent and short fixations imply a low level of attention and processing, such as screening, more frequent and longer fixations are associated with frequent reorientation and deeper processing, such as the deliberate consideration of information (Nummenmaa et al., 2006; Glöckner and Herbold, 2011) and a greater weight of the feature for decision-making processes (e.g., Fisher, 2017). Furthermore, eye-tracking also allows for the measurement of preferences while being relatively unobtrusive, i.e., the person being observed acts naturally within the environment (Glaholt et al., 2009). Importantly, research has repeatedly identified visual focus as a causal predictor for choice (e.g.,

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[1] Although the terms are often used synonymously in the literature, we will use visual focus only to highlight our way of measuring attention.

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Fisher, 2021; Bhatnagar and Orquin, 2022). Another approach to learning about people's attention to information displayed on screens is mouse tracking, where information becomes accessible only when the person moves the cursor of the mouse over certain parts of the screen, e.g., applied recently by Bhui and Jiao (2023), which can provide complementary information regarding choice prediction (Fisher, 2025). However, the use of biometric data as an indirect proxy of attention in studying financial decision-making is not without limitations. For instance, the visual salience of certain elements may subconsciously influence visual focus, or the fixation duration might differ conditionally on the complexity of screen elements.

In contrast to eye tracking, the active selection of information elements allows researchers to investigate attention in a different way. An information element may not attract substantial visual focus; yet, it can hold essential significance for informed decision-making. Therefore, the selection approach can assess the overall information need for various information elements (Teschner et al., 2015). However, this measure offers insights solely into how these selections impact financial outcomes on an ex post basis; i.e., it provides no insights into the underlying dynamic processes before traders make trading decisions.

Note that there are different aspects of engagement. Emotional engagement, e.g., can be measured by using heart rate changes and electrodermal activity. In a trading context, Bossaerts et al. (2024) demonstrate that anticipatory heart rate changes are associated with better performance, while reactive changes in response to financial events lead to poorer performance.

Motivated by the question of how visual focus and the active selection of screen elements impact financial decision-making, we combine these two approaches and analyze traders' behavior when visually processing *and* selecting information elements in a unique experimental asset market setting. Please note that our study does not delve into the influence of trading interface design on attention and behavior. In our study, the trading interface is a tool for conveying information. Subsequently, we control several aspects of the screen design (e.g., standardized box sizes, randomized box positions, and no attention-grabbing colors). We analyze dynamics in visual focus and choice rather than proposing optimal trading interface designs for enhancing trading performance or price efficiency. Thereby, we investigate three research questions.

Research Question 1. *How do asset market designs and personal characteristics influence traders' visual focus and the selection of information elements?*

Research Question 2. *How do traders' visual focus and the selection of information elements change within and across periods?*

Research Question 3. *Where does traders' visual focus rest before trading decisions, and is there an association with trading performance?*

To address these research questions, we run laboratory asset markets. The trading interface on which traders interact, consists of one action field for submitting limit and market orders and six information elements: the personal order history, the order book, the price chart, the inventory field, a field for information signals, and the time clock. Within this setting, we first vary whether traders have access to a standard interface displaying the *complete* set of all six information elements (treatment **CPL**) or can choose a *limited* set of information elements (treatment **LTD**). Second, we use two established experimental asset market designs, i.e., the Smith et al. (1988) bubble market setting (**SSW**), and the Plott and Sunder (1988) information aggregation setting (**PS**), to assess to what degree visual focus and element selection vary with the underlying asset market design and their distinct features.

With a set of additional tasks and questionnaires, we elicit participant-specific characteristics to augment the analyzes (see Krefeld-Schwalb et al., 2024, for a motivation to include comparable measures in the analysis). Thereby, our study closely relates to the literature on the effect of personal characteristics, such as gender, risk attitude, and cognitive capabilities on trader performance (Charness and Gneezy, 2007; Eckel and Grossman, 2008; Eckel and Füllbrunn, 2015; Corgnet et al., 2018, 2021). Shedding new light on these findings, our study aims to assess whether the visual focus on, or the selection of information elements, correlates with personal characteristics.

Analyzing the data from four treatments that differ with respect to the access to information elements and/or the asset market design reveals four main insights. First, we find that among the information elements, traders mainly visually process and select the order book, regardless of the underlying asset market design. Furthermore, traders frequently examine the order book right before making trading decisions. In contrast, the price graph is neither among the three most frequently selected elements nor does it receive a lot of visual focus (less than 5%), even in bubble-prone market settings. The price chart also receives little visual focus before traders place or accept orders. These results indicate that the average trader does not focus on past prices to base their decisions on but rather pays attention to the liquidity displayed in the order book and the information that the aggregate collection of limit orders might convey.

Second, our results show that the traders' visual focus on information elements conditionally aligns with the set of selected information elements. This observation implies that eye-tracking is partly a reasonable proxy for the set of actively selected elements in the limited trading interface. However, there are notable differences between visual focus and element selection concerning two informational elements. While the inventory field is the most frequently selected information element, it receives little visual focus before trading decisions and throughout the experiment. This observation implies that traders do not primarily look at the inventory field, although they consider it indispensable for trading. In contrast, the order book receives more visual focus before trading decisions and throughout the experiment; however, it is selected less frequently than the inventory field, reflecting traders' high engagement with visual focus toward the order book.

Third, we find that specific trader characteristics correlate with the selection of, and visual focus attributed to, certain information elements, depending on the employed element and the underlying asset market design. In particular, we report that high cognitive skills correlate positively with the order book, negatively with the order submission field, and negatively with the inventory field, depending on the treatment condition.

Fourth, our evidence of a potential link between visual focus and trading performance is mixed. We find that a stronger focus on the order book correlates positively with performance, while a stronger focus on the order submission box correlates negatively, again depending on the underlying asset market design. While the order book naturally serves as the interface for trade execution, its informational relevance extends well beyond this operational role. It provides continuous signals about market depth, liquidity, and other traders' intentions. Our study, therefore, examines attention to the order book as part of an integrated decision-making process, capturing both informational and operational dimensions of trader behavior. Although these aspects cannot be perfectly disentangled in real time, their joint observation offers valuable insights into how traders process information and prepare for market actions.

2. Related literature

Our paper connects the eye-tracking literature in asset markets with the literature studying the selection and combination of information elements. Subsequently, we contribute not only by evaluating the importance of information elements in financial decision-making on an ex-post basis but also by investigating the dynamic processes via eye tracking that drive traders' behavior in markets. In this section, we provide an overview of both research strands and outline how our work contributes to the literature.

The increasing availability and affordability of eye-tracking technology have allowed for its application in various economic studies (see Lahey and Oxley, 2016, for a review). In the field of marketing and consumer choice, Reutskaja et al. (2011) investigate which kind of snack items attract consumers' attention under time pressure. They show that the choice process is subject to display effects. In other words, the probability of an item being selected depends on its location. Furthermore, when faced with a limited budget, consumers show increased attention before making purchasing decisions (Amasino et al., 2023). Glöckner and Herbold (2011) focus on information processing in risky decision-making by comparing eye movements to probabilities and payoffs in risky gambles. Their results suggest that risky decisions are more likely to rely on automatic intuition rather than on a weighting and summing process. Glaholt et al. (2009) examine the relationship between visual fixation and selection during preference decisions. They find that visual fixation on a particular stimulus is positively correlated with the likelihood of that item being selected. Drawing upon eye-tracking data from a previous study, Hirmas and Engelmann (2023) found that the duration of visual focus affected traders' sensitivity to specific cues in a risky decision environment. Further, when faced with risky decisions on behalf of others, individuals spend less time fixating and inspecting relevant information (Barrafrem and Hausfeld, 2020). Preference reversals could also be linked to specific gaze patterns, indicating attentional shifts (Alós-Ferrer et al., 2021; Alós-Ferrer and Ritschel, 2022).

In recent years, eye-tracking has also emerged in the field of financial research as a promising tool for studying investment decision behavior. Bose et al. (2022) and Tank et al. (2021) both use eye-tracking to study how the visualization of a single information element can impact investment decision-making. Tank et al. (2021) focus on bar charts that illustrate company earnings. They find that adapting the scale, by switching from yearly to quarterly reporting frequency, influences the perceived attentiveness of investment and correlates positively with the amount traders are willing to invest in a company. Bose et al. (2022) employ a machine learning algorithm trained on eye-tracking data to predict the visual salience of price charts. They present evidence that investors assign decision weights to past returns based on the visual salience of the respective price chart area and demonstrate how these decision weights can contribute to explaining investment decisions.

In contrast to the aforementioned eye-tracking studies, Powell (2010) allows traders to use different information sources besides only charts in a bubble market setting. His findings suggest, with weak evidence, that crashes are immediately preceded by an absolute decline in attention to purchasing opportunities. Furthermore, he finds that male traders focus more time on textual information regarding prices rather than on actual dividends.

Finally, Toma et al. (2023) analyze whether eye-tracking bio-metric indicators (arousal, attention, and disengagement) can influence and predict individual payoffs in a bubble market setting. They find that attention and arousal are positively correlated with individual returns when subjects look at a stock price graph, while disengagement can negatively impact returns.

Another related line of research explores the structuring of information and its relevance for trading performance. As information overload can cause individuals to lose focus (Gross, 1964), scholars have highlighted the importance of achieving a *"cognitive fit"* between the format in which information is presented and the nature of the problem-solving task. Such alignment facilitates more efficient processing by working memory (Vessey, 1991, p. 64). Consequently, using an appropriate presentation format enhances mental representations of the problem, thereby improving problem-solving outcomes. Extending this perspective, Beunza and Stark (2004) conduct an ethnographic field study in a Wall Street trading room, illustrating how successful traders manage the challenges posed by information overload. Their findings emphasize that effective traders are skilled at identifying relevant information and interpreting its significance. As a result, traders *"individually tailor their digital workbenches"* (p. 390) to suit their specific needs.

Experimental research supports these findings by showing that the selection and/or different combinations of information elements can significantly impact trading performance. Teschner and Weinhardt (2012) study the differences between static trading screen designs in a field experiment involving 600 traders. They find that traders relying on a simplified trading interface are more likely to submit profitable orders than those using the standard interface. In a related study, Teschner et al. (2015) evaluate the effects of a customizable trading interface on trading performance in a field experiment with 800 traders. They find that the limit order book is the most frequently selected screen element (95%) before an order is submitted. Furthermore, they find that presenting more information does not improve decision-making but rather decreases trading performance. Finally, they show that screen elements such as the order book, personal order history, and market information positively influence trading performance, while the price chart exerts a negative impact. Taken together, these findings suggest that successful traders do not base trading decisions on historical trading data but rather focus on the general liquidity displayed in the order book.

In addition to focusing on visual focus, our paper also relates to the literature on personal characteristics and trading performance. Charness and Gneezy (2007) as well as Eckel and Grossman (2008) both present evidence that women are found to exhibit a higher degree of risk aversion in investment games than men. Eckel and Füllbrunn (2015) find a gender difference in producing speculative price bubbles. Corgnet et al. (2018) provide evidence that cognitive capabilities, such as cognitive reflection skills and fluid intelligence, influence trader performance by enabling them to avoid behavioral biases, which in turn allows them to extract signals from market orders and update their prior beliefs. Similarly, Corgnet et al. (2021) show that cognitive capabilities are important for ensuring the informational efficiency of markets because they enable traders to infer others' information from prices.

3. Research design

In the context of decision-making, attention can be broadly categorized into two distinct mechanisms: *top-down attention*, guided by the decision-maker's internal goals and expectations, and *bottom-up attention*, driven by salient external features of the stimuli (Engelmann et al., 2021). Given our focus on goal-directed attentional processes, the experiment aligns with the top-down framework, in which differences in information access and asset market design play a central role in shaping attentional allocation. While visual focus could also indicate stimulus-driven attention, the goal-driven nature of our task likely overwrites these bottom-up processes (Orquin and Mueller Loose, 2013), particularly when task demands are present and rewards relate to performance (Kowler, 2011).

To this end, we implement a 2×2 between-subjects design, varying (i) the access to information elements (see Section 3.1) and (ii) the underlying asset market design (see Section 3.2). We employ a between-subjects design rather than a within-subjects design for two main reasons. First, between-subjects designs feature shorter sessions and, therefore, align better with the specific requirements of eye-tracking procedures. Normally, such studies last only 20 to 30 min, as participants' attention spans significantly decrease afterward. Second, we can control for fatigue and learning effects that might otherwise weaken the internal validity of our study. With this design, we can provide a comprehensive picture of the relationship between information elements, factors impacting visual focus, and trading decisions.

3.1. Trading interfaces and the access to information elements

The trading interfaces (see Figs. 1 and 2) employed in the experiment feature one action field and six information elements. The action field allows participants to submit limit and market orders. The information elements are (i) the personal order history, (ii) the order book, (iii) the price chart, (iv) the inventory field, (v) the signals field, and (vi) the time clock. We chose these seven elements based on an analysis of the frequency of information elements in experimental asset market papers (given that they are graphically displayed in the respective paper). Also, the choice of information elements closely resembles the available options in Teschner et al. (2015). In their experiment, participants can customize the trading interface with up to six or seven information elements, depending on the underlying round, including: (i) the personal order history (referred to as previous predictions, only available in the second round), (ii) the order book (referred to as current bids), (iii) the price chart (referred to as price development), (iv) the inventory field (referred to as my account), (v) the signals field (referred to as economic news), (vi) the field market information (features last trading price and last trading day), and (vii) the field historical values (features previous year's asset performance).

We intentionally refrain from making prior assumptions about the relative importance of specific information elements to participants. By presenting all elements uniformly, we allow participants to determine for themselves which types of information they consider most valuable. Some may prioritize the inventory, fundamental value signals, or price charts, while others may focus on the order book, time clock, or personal order history. Our approach is designed to offer a comprehensive representation of the available information without imposing normative judgments regarding the relevance of particular elements.

When examining the trading interfaces (Figs. 1 and 2), one can observe several boxes (fields), which we describe in the following. The action (or order submission) field provides participants with information about the current best bid and best ask. The upper box enables participants to submit limit orders, while the lower box allows for the placement of market orders. Additionally, participants can withdraw their orders via the action field if their order represents the current best bid or best ask. All other outstanding orders – apart from the best bid or ask – can be canceled only through the order book, which is a standard feature in laboratory asset markets. Allowing participants to withdraw their orders introduces greater flexibility in decision-making and enhances the realism of the trading environment. As such, the order book may be interpreted as a hybrid element, serving both informational and transactional purposes. If the order book is not selected, only the current best bid and ask can be canceled via the action field, and only if they were submitted by the respective participant.[2]

To inform participants about past prices, the trading interface features a price chart rather than a table because graphs outperform tables when tasks require comparing data and understanding relationships (Kelton et al., 2010). Consistent with the predictions of cognitive fit theory, graphs are better suited for visualizing the relationships between the data because they display it as an integrated unit rather than as discrete data values (Vessey, 1991). The choice is further supported by Glaser et al. (2019) who highlight that over 90% of financial information providers incorporate price charts into their offerings and the documented influence of investor decisions (Bose et al., 2022; Grosshans and Zeisberger, 2018; Nolte and Schneider, 2018). Finally, illustrative content can strongly attract humans' attention, requiring cognitive efforts to divert focus to other elements (Sanchez and Wiley, 2006).

The signals table contains information that is important for the valuation of the asset. In our study, the signals vary substantially across asset market designs. In one market design, it contains private information relevant to the current period, while in the other, it reflects publicly known information across all periods (for a more detailed discussion, see Section 3.2).

In designing the interfaces, we avoid attention-grabbing colors for information elements and, therefore, set the background color to gray. We highlight the order submission as an action field due to its fixed central position and light purple color. The letter font size is set to 12-point font and is the same for all information elements. Furthermore, we standardize the size and shape of the elements, i.e., the box dimensions are rectangular and of the same size for the outer information elements and the same size for the action field and information elements in the center of the screen. Moreover, we control for the possibility of display effects (Reutskaja et al., 2011) when determining the location of elements on the screen.

By using a random procedure, we predetermine the positions of the information elements on the screen so that each participant likely sees a trading interface with differently located information elements. In particular, the implemented procedure separately determines the positions of the four information elements located to the left and right of the order submission field and the two information elements located above and below the order submission field. Therefore, the size of information elements is kept constant for all participants, and elements with buttons are located in the middle column. The order submission field represents an action field and, therefore, is accessible at all times and remains in the center of the screen without changing its position.

Positioning the action field in the center of the screen might trigger a center bias, implying that elements in the middle of a screen attract more attention (Tatler, 2007). Although this should primarily impact initial fixations (Bindemann, 2010; Tatler, 2007), participants may be more strongly drawn to this screen element because it is an action field and is more visually salient. Note, however, that we are particularly interested in evaluating the visual focus attributed to the information elements located in random order around the center. Given the fixed position of the action field in all treatments and assuming that center bias does not vary systematically between treatments, we can reasonably compare the differences in visual focus attributed to the different information elements. Thus, we can draw meaningful conclusions about how participants prioritize and allocate their attention within the trading interface.

Study participants are randomly assigned to one of two treatments that differ in the number of information elements available on the trading interface. Participants do not know the treatment to which they have been assigned. During a session, all participants are either in treatment CPL in which they have *complete* access to all information elements (see Fig. 1) or in treatment LTD in which participants only have *limited* access to the information elements (see Fig. 2).

In each period of LTD, participants can choose up to three (out of six) information elements by clicking on an "ON" button for the respective information element. In their experiment, Teschner et al. (2015) find that subjects open, on average, three out of six (respectively seven) information elements. Therefore, we consider three elements to be a meaningful upper bound for our parameter choice. After three information elements have been chosen, the remaining "ON" buttons automatically disappear, and the other elements remain concealed for the rest of the period. There is no obligation to open any elements. Note that participants can reconsider their selection of information elements at the beginning of each period, allowing them to choose up to three items anew. However, once selected, the information element remains open for that particular period.

In both treatments, we attach a monitor-based eye tracker at the bottom of the monitor and provide a chin rest to participants to stabilize their eye movements. Thereby, we ensure that any differences across treatments are driven by the design of the trading interface and not by the use of eye trackers.

[2] Out of the 4751 submitted orders, 451 were cancellations, constituting approximately 9.5%.

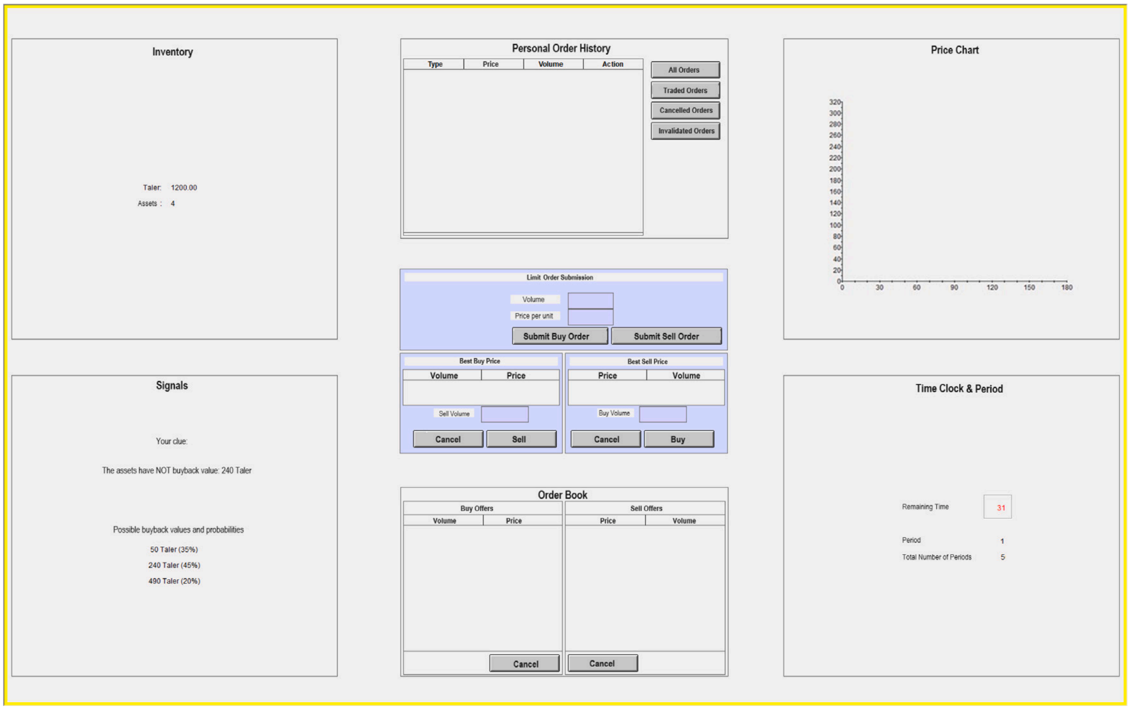

Fig. 1. Trading Interface for CPL.

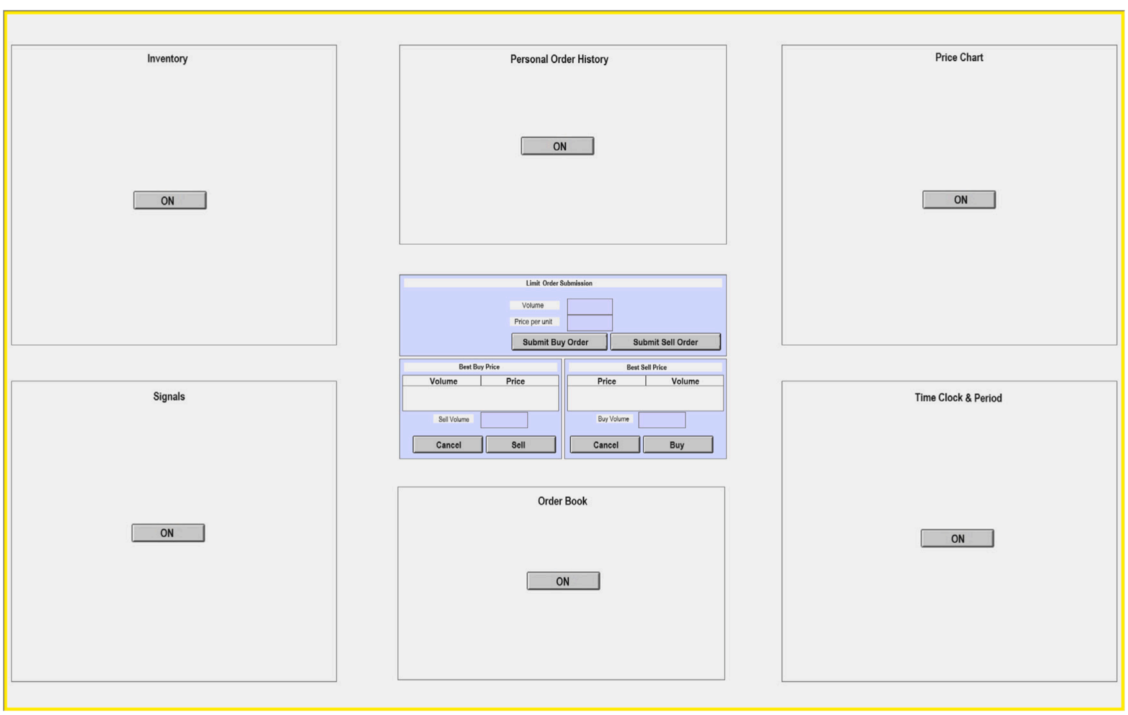

Fig. 2. Trading Interface for LTD.

3.2. Asset market designs

We analyze our research questions based on data elicited from two well-established experimental asset market designs. The first design is the Smith et al. (1988) bubble market setting (SSW hereafter), and the second is the Plott and Sunder (1988) information aggregation setting (PS hereafter). By using two designs, we are able to investigate how participants' visual focus on information elements and the selection of information elements vary with the underlying asset market design and their distinct features, e.g., the dissemination of information (private or public knowledge), different time horizons (single or multi-period), and asset value characteristics (decreasing fundamental values, FV, or state-contingent dividends, SCD). Furthermore, the paper relates to two prevalent strands of the literature that work on two different aspects of interest in financial market research.

By following this approach, we strengthen the paper's contribution compared to the results gained from a study with a single experimental market design (Huber et al., 2023). While both experimental designs

Table 1
Overview of asset market designs and the number of observations.

	SSW	PS
Parameters	Design 4 as in SSW (1988)	Market 9, Treatment C as in PS (1988)
Information Dissemination	Public knowledge	Public knowledge + Private signal
Inventory Horizon	Multi-period; carryover	Single period; periodic reset
Asset value characteristics	Decreasing fundamental value	State-contingent dividends
Trading periods	2 trial, 10 trading periods	2 trial, 5 trading periods
Trading Phase (seconds)	120 s	240 s
Information elements	CPL: 6/6; LTD: 3/6	CPL 6/6; LTD: 3/6
# Cohorts (Markets)	CPL: 4; LTD: 4	CPL 4; LTD: 4
Cohort Size	9 participants	9-10 participants
# Participants (total)	CPL: 36; LTD: 36	CPL 39; LTD: 40

Table 2
Endowment types in SSW.

	Type I	Type II	Type III
Number of traders	3	3	3
Stocks	3	2	1
Taler	240	480	720
Initial wealth	960	960	960

relate to real world trading situations, the usual disclaimer concerning the level of external validity of laboratory asset markets applies. Note, however, that studying two market designs contributes to strengthening the internal validity of the reported results.

Table 1 provides an overview of specific parameters for these two asset market designs and the number of observations. In both designs, we have two trial periods to allow participants to accommodate themselves to the trading mechanism and the incentive structure. In our implementation, we use the design parameters from the original papers, with adjustments regarding the total number of periods. The sessions in SSW and PS consist of fewer periods due to time constraints. Nyström et al. (2013) note that a gradual decline in eye calibration can occur as the study progresses. In addition, the participant's attention span and, thereby, the quality of the eye-tracking data may decrease as time goes by. Lahey and Oxley (2016) also recommend that eye-tracking tasks should take no longer than 30 min.

In SSW, we study markets with a declining FV and therefore use the classic Design 4 parameters as in the original (Smith et al., 1988) setup. Palan (2013) provides a detailed review of studies based on this design. In each market, nine participants can buy and sell multiple units of a risky asset against experimental currency (taler hereafter) in a multi-unit continuous double auction with an open order book over a sequence of ten periods of 120 s each. We follow standard practice in the SSW literature by having three endowment classes. Valued at the fundamental value of the asset, each participant has the same initial wealth. The distribution of initial endowments is summarized in Table 2.

SSW is a multi-period model, as taler and asset holdings are carried over from one period to the next. The asset pays a dividend of either 0, 8, 28, or 60 taler with equal probability at the end of each period. The asset's fundamental value in period 1 is 240 taler and decreases by the expected dividend of 24 taler each period. After ten periods, the asset's fundamental value is zero, which is public knowledge. No interest is paid on taler holdings, and there are no transaction costs. Short selling and borrowing money are not allowed. At the end of the market, the final payoff equals the amount of taler participants have at the end of the final period after the last dividend has been paid.

For the design studying a market's ability to aggregate diverse information, PS, we replicate the setup of Treatment C in Plott and Sunder (1988) and Corgnet et al. (2018). In each market, ten participants can buy and sell multiple units of a risky asset for taler in a multi-unit continuous double auction with an open order book over a sequence of 5 periods of 240 s each. Participants are endowed with 1200 taler in cash and four assets. PS is a single-period model, as taler and asset holdings are not carried over from one period to the next. We follow standard practice in the PS literature by having three possible dividend states. The asset pays a dividend of either 50, 240, or 490, with probabilities of 0.35, 0.45, and 0.20 at the end of each period. At the beginning of each market period, every participant is informed of one value that the dividend will *not* take. Since half of the participants are given one hint (e.g., "Not 50") and the other half are given the other possible hint (e.g., "Not 240"), the aggregate information available to all participants in the market is complete, and in a rational expectations equilibrium, prices should reflect the true dividend of the asset (for the example, 490). No interest is paid on taler holdings, and there are no transaction costs. Short selling and borrowing money are not allowed. Participants' payouts are the cumulative payoff of all five periods.

3.3. Elicitation of personal characteristics

Before the main experiment, participants complete certain standard pre-experimental tasks. We run these tasks before the market periods to avoid the scales being influenced by the outcomes of the markets. In particular, the tasks consist of the seven-item Cognitive Reflection Test (Frederick, 2005), the advanced fluid intelligence test consisting of 18 matrices (Raven, 1941), a 12-item test of financial literacy (van Rooij et al., 2011), and the social value orientation task (Murphy et al., 2011; Crosetto et al., 2019). We provide screenshots of these tasks in Figures OAF25 and OAF26 in the Online Appendix.

To assess participants' tendency to decide intuitively or reflect before answering, we employ the seven-item Cognitive Reflection Test (CRT; Frederick, 2005). The CRT focuses on participants' cognitive reflection skills and ranges from zero to seven. It is the same set of quantitative questions as used in Corgnet et al. (2018). For each correct answer, participants receive 2 taler. They are not penalized for wrong answers and may choose not to answer. Participants can score a maximum of 14 taler and a minimum of 0 taler. The payoff from this section is added to the total earnings. In total, participants have three minutes to answer the questions, and they must submit their answers before the time is up, otherwise, they receive no payoff from this section. In our experimental design, we set an automatic timeout for the CRT task in our software so that participants would submit their answers in a timely manner. Unfortunately, many participants did not submit their answers in time; thus, their CRT score was not recorded correctly. Thus, we omit observations with a score of 0 in our analysis, implying that the number of observations for CRT is lower than the number of participants in CPL and LTD of the SSW design, as well as CPL of the PS design. We changed the automatic time-out in later sessions of the PS design, in which participants had to submit their answers to continue to the next question.

As a measure of fluid intelligence, we employ 18 items from the Advanced Progressive Matrices (APM; Raven, 1941). In contrast to CRT, the Raven APM intelligence test measures one's capacity to compute solutions to problems but fails to assess one's capacity to engage in reflection (Stanovich, 2009; Corgnet et al., 2018). In short, the former assesses cognitive reflection, while the latter is more related to cognitive ability. For each correctly solved matrix, participants receive 2 taler. They are not penalized for incorrectly solved matrices and may choose to skip the matrix. Participants can score a maximum of 36 taler and a minimum of 0 taler. The payoff from this section is added to the total earnings. In total, participants have ten minutes to solve the matrices.

To assess participants' financial literacy, we employ the 12-item test of financial literacy (FLS; van Rooij et al., 2011). For each correct answer, participants receive 2 taler. They are not penalized for wrong answers and may choose not to answer. They can score a maximum of 24 taler and a minimum of 0 taler. The payoff from this section is added to the total earnings. Participants have three minutes to solve the first six questions and an additional three minutes to solve the remaining six questions.

Finally, we elicit participants' social value orientation (SVO; Murphy et al., 2011) by assessing the distribution of financial outcomes between the decision-maker and others, thereby ranking social preferences on a continuous scale. The underlying process can be described as six dictator games in which the decision-maker can allocate a predefined sum of money to oneself and the other party. The decision outcomes can be summarized via the SVO index. The SVO calculates the ratio of the average payoff allocations to others to the average payoff allocation to oneself. High values indicate altruistic and prosocial orientations, while low values imply individualistic or competitive preferences. We employ the social value orientation slide measure developed for z-Tree (Crosetto et al., 2019) and use their ring matching protocol. Subsequently, each decision-maker is both sender and receiver; however, in each role, she is matched with a different person, i.e., A gives to B, B gives to C, C gives to D, and D gives to A. The computer randomly determines one of the six choices made for the payout as a sender and another randomly determines one of the six choices made for the payout as a receiver. The earnings in this task are the sum of the amount the participant received as a receiver and the amount the participant kept as a sender, divided by 4. The payoff from this section is added to the total earnings. In total, participants have three minutes to complete the social value orientation task.

After the pre-experimental tasks but before the market experiment, we ask participants to provide information regarding gender (binary), age (continuous), educational science background in economics (binary), current major in academic studies (nominal), trading experience (binary), former participation in experimental studies (binary); general risk attitude (scale 1–7); stock market-specific risk attitude (scale 1–7). Participants receive no payoff for providing this information.

3.4. Implementation

We conducted the experiment in German language from April to November 2022. The software is based on the GIMS asset market software (Palan, 2015) in z-Tree (Fischbacher, 2007). Participants were recruited via the *Online Recruitment System for Economics Experiments* (ORSEE; Greiner, 2004). In Table OAT1 of the Online Appendix, we present the demographic and behavioral characteristics of participants across the four treatments. In accordance with experimental procedures, subjects needed to sign a consent form before participating in the experiments at the Lakelab. Participants may have previously participated in other economic experiments but each participated only once in this study. In total, we conducted 16 sessions and our sample consists of 151 randomly selected university students from business-related disciplines. One cohort equals one market observation: 2 asset market design SSW $\times$ 4 cohorts $\times$ 9 participants +2 asset market design PS $\times$ 4 cohorts $\times$ 10 participants = 152 participants). In one cohort of PS CPL, we only had 9 rather than 10 participants due to participant no-shows.

We chose a research laboratory to conduct our study which is equipped with the necessary eye-tracking technology, namely ten Tobii EyeX devices. Alignment and calibration (7-point calibration technique) of the participant's eyes only take a very short amount of time (usually up to 20 s), and the participant's head movement is controlled via a chin rest, positioned at a normal distance from the screen (approximately 58 cm). These conditions align well with our study, which only requires static eye-tracking (rather than mobile eye-tracking). Finally, it is possible to set time marks during the eye-tracking process, thereby aligning eye–tracking with the staged structure of z-Tree experiments.

Participants received a show-up fee of €5 and earned, on average, €23 (including the show-up fee) for participating in the experiment, depending on their performance in the pre-experimental tasks and the market experiment. Additionally, they received €5 for using the eye-trackers in the market experiment, independent of their performance in this experiment. Participants were at least 18 years old. Sessions lasted for approximately 70 to 80 min (25 to 35 min for instructional and organizational procedures, 20 min for completing the pre-experimental tasks (no eye-tracking), and 25 min for the market experiment with eye-tracking). Participants received the printed instruction sheets in German language. Before the start of the market experiment (eye-tracking), the experimenter recollected the instruction sheets in order to better record participants' eye movements.

4. Hypotheses

With the data generated by the experiment, we evaluate nine individual hypotheses, which we group into three sets. In March 2022, we pre-registered our hypotheses, design, sampling, and analysis plan on the Open Science Framework (information hidden during the review process).[3]

Hypotheses set 1 (Section 4.1) links to RQ 1 and analyzes the influencing factors on participants' visual focus and selection of information elements. It comprises Hypotheses 1, 2, and 3. Hypotheses set 2 (Section 4.2) links to RQ 2 and studies how the visual focus and selection of information elements change over time. It comprises Hypotheses 4, 5, and 6. Hypotheses set 3 (Section 4.3) links to RQ 3 and investigates how the visual focus influences trading decisions and trading performance. It comprises Hypotheses 7, 8, and 9.

Note that in continuous double-auction markets, the informational and operational motives for attention often coincide. Monitoring the order book conveys informational content about the current state of the market while simultaneously enabling execution decisions. We therefore interpret eye movements as reflections of an integrated cognitive–operational process rather than as distinct sequential stages of information acquisition and execution. This view aligns with recent approaches emphasizing the dynamic coupling of perception, decision-making, and action in financial trading contexts.

4.1. Hypotheses set 1 – Influencing factors

The selection of information elements and participants' eye fixations (our measurement of visual focus, see Section 5.1) both provide insights into how participants consider information; however, they differ in a substantial way. Whereas the active selection of screen elements reflects the overall need for certain information sources (i.e., which information elements are indispensable for trading), eye fixations reflect the engagement of attention toward a stimulus (i.e., which information elements are primarily processed). Put differently, participants may not primarily focus on an information element, but still consider it important for investment decisions. In CPL, participants have access to all six information elements, while in LTD, participants can choose the most relevant information elements according to their needs. Consistent with previous research examining the relationship between eye movements and selection during preference decisions (Glaholt et al., 2009),

[3] All nine hypotheses have been pre-registered; none have been omitted or dropped. During the writing process, the order of the hypotheses has been adapted, and some wording has been refined. For example, "attentional focus" has been refined to "visual focus".

and findings of visual attention causally predicting choice (Bhatnagar and Orquin, 2022) we assess whether participants' visual fixations on information elements in CPL correspond to the most frequently selected elements in LTD.

Hypothesis 1. Recognized and Selected Elements: Participants' visual focus on information elements recognized in CPL correspond to the most frequently selected elements in LTD.

As different experimental procedures, design choices, and research interests may trigger different outcomes in exchange and trading experiments (Plott and Zeiler, 2005), we also expect differences in participants' visual focus on information elements between the SSW bubble market setting and the PS information aggregation setting.

Hypothesis 2. Asset Market Design: Participants' visual focus on and the selection of information elements differ between the SSW bubble market setting and the PS information aggregation setting.

Considering that participants with higher cognitive capabilities can better extract and interpret signals from market activity than participants with lower cognitive capabilities (Corgnet et al., 2018), we expect participants' visual focus on and selection of information elements to depend on personal characteristics.

Hypothesis 3. Personal Characteristics: Participants' visual focus on and the selection of information elements correlates with personal characteristics.

4.2. Hypotheses set 2 – Time trends

Considering the results of Teschner et al. (2015), we assume that participants' behavior likely changes across periods. In particular, inexperienced participants might rely on different information elements and gradually learn, which information elements best address their needs. To study this behavior, we determine a convergence parameter by computing the absolute difference in fixation counts for each information element between two periods. If this parameter decreases over the course of the experiment, we interpret this as a learning effect. Moreover, we also expect personal characteristics to impact the convergence toward the set of visually recognized information screen elements.

Hypothesis 4. Time Trends across Periods — Convergence I: Participants' visual focus on and the selection of certain information elements will converge over the course of the experiment.

Hypothesis 5. Time Trends across Periods — Convergence II: Personal characteristics impact the convergence toward the set of recognized information elements.

While some information elements present static information during a trading period, other information elements present continuously updated information, i.e., they change their informative content over time. For example, the signal table always features the same information within a period, while the order book, price chart, personal order history, time clock, and inventory field continuously change. We expect participants to shift their visual attention from static to dynamic information elements during the course of the period, allowing them to focus primarily on new arriving information.

Hypothesis 6. Time trend intra-period – Convergence III: Participants' visual focus will transition from static to dynamic information elements during the trading period.

4.3. Hypothesis set 3 – Trading outcomes

Zaloom (2003) highlights the importance of understanding market actions and states that participants look for clues about market direction by observing the numbers. Similarly, Beunza and Stark (2004) describe how arbitrage participants use specialized instruments to continuously track market activity. Hence, we also expect that trading decisions made via the order submission tool are preceded by an increase in attention to elements tracking recent market developments.

Hypothesis 7. Trading Decisions: Market tracking elements (order book; price chart) receive more visual focus than non-market tracking elements before participants place or accept orders (limit orders; market orders).

Building on Corgnet et al. (2018), we assess whether a higher visual focus on certain information elements correlates with trading performance. We hence formulate:

Hypothesis 8. Trading Performance I: Participants' visual focus on certain information elements correlates with their trading performance.

Hypothesis 9. Trading performance II — Mediator: Participants' visual focus on information elements mediates the relationship between interpersonal characteristics and trading performance.

Since the results are significant only in one treatment and difficult to interpret, we report the analyzes related to Hypothesis 9 in section 2.2.2 of the Online Appendix.

5. Measurement

We employ Tobii EyeX near-infrared eye-tracking sensors to measure participants' gaze behavior at a sampling rate of 70 Hz. 7-point calibrations were conducted before the main experiment and validated via an algorithm integrated in the eye-tracking software that required re-calibrations in case of insufficient accuracy of the detected gaze points. The task only commenced if all calibrations were successful. To control for learning effects in the experiment, we started the eye tracking recordings only after the two initial trial periods. In one cohort of PS CPL, we had only 9 participants instead of 10 due to participant no-shows. In one cohort of SSW CPL, the eye tracking recording terminated in the last round of trading for one participant. We consequently excluded this participant's data for the last round from all data analyzes. Additionally, we manually checked calibrations before the further processing of data and noticed a systematic deviation of gaze coordinates from their expected location for one participant, which we were able to correct.

To calculate fixations from our raw eye-tracking data, we employ a density-based clustering algorithm (Ester et al., 1996; Hahsler et al., 2019) to identify clusters of gaze points within a certain area. As a minimum threshold for classifying fixations, we select a duration of 100 ms (Salvucci and Goldberg, 2000) and vertical and horizontal spatial proximity of 50 pixels (Hausfeld et al., 2020; Koch et al., 2021), which corresponds with the recommendations of a fixation radius of about 1° at a distance of approximately 60 cm (Blignaut, 2009).

5.1. Fixation parameters

In this paper, we aim to provide insights into the engagement of attention and how long it takes to process the stimulus at that location. Therefore, our metrics of interest are participants' fixation count, their fixation duration (in seconds), and the fixation frequency within the seven predefined areas of interest, i.e., the seven information elements (one action field and six information elements).

Our first parameter, *fixation count*, measures the number of fixations within each of the seven screen elements. Our second parameter, *fixation duration*, measures the length of fixations in seconds within each of the seven screen elements. While an increased fixation count indicates the importance of a stimulus for the decision maker (e.g., Glöckner and Herbold, 2011; Su et al., 2012), differential encoding of stimuli (Glaholt and Reingold, 2011), a frequent (re-)orientation of the visual focus toward the area, as well as information aggregation (Horstmann et al., 2009), fixation duration corresponds with sustained visual engagement and processing within an area of interest (Maran et al., 2019; Nummenmaa et al., 2006; Sáiz-Manzanares et al., 2021). To facilitate comparison, we report both of these measures as percentages of the total fixation count or duration, respectively. Our third parameter, *fixation frequency*, measures the number of fixations per second, which can further indicate comparison processes (Glaholt and Reingold, 2011). We calculate the fixation frequency by dividing the fixation count on a specific element by the total number of seconds in the respective period. By adjusting for the difference in period length, we can allow for direct comparability between our asset market designs.

The three fixation parameters are highly correlated (r = [0.60; 0.98] for the SSW CPL, r = [0.76; 0.98] for SSW LTD, r = [0.73; 0.97] for the PS CPL market, r = [0.74; 0.98] for the PS LTD market). These intervals depict the upper and lower bounds of the intercorrelations between the three eye tracking parameters directed at the same area. For example, the relative fixation count on the inventory field in the SSW CPL condition correlates with the relative fixation duration on the same area at r = 0.60, which was the lowest intercorrelation of eye tracking parameters on the same area in SSW CPL and therefore constitutes the lower bound of the interval.

Depending on the hypothesis, our three parameters are calculated at an aggregate level for all four treatments together or separately for each treatment (CPL and LTD of the SSW design, and CPL and LTD of the PS design).

To account for the heightened relevance of the order submission field resulting from its increased visual salience, central positioning, as well as its role as an essential action field, we also replicate our main analyzes for fixation count, excluding the order submission field when computing the relative fixation counts. We report these results in section 2.2.1 of the Online Appendix.

For the sake of simplicity and because of the high correlations, we only report fixation counts within the main text, but provide statistics based on the fixation duration and frequency in the Online Appendix as robustness checks (see section 2.2.2).

5.2. Data analyses

To compare the distribution of traders' eye gaze between reasonable combinations of treatments (CPL and LTD) and market designs (SSW and PS), we computed independent samples t-tests for fixation count, duration, and frequency, using percentages for fixation count and duration to ensure comparability between treatments. Furthermore, we compared the gaze behavior of traders' scoring among the highest 20% in the APM task, which indicates high fluid intelligence, to those in the lowest 20% across all markets, again employing independent samples t-tests. Lastly, to analyze the convergence of traders' gaze behavior across periods, we compared fixations in the first 120 s (which equals the first two periods in the SSW or the first period in the PS design, respectively) to those exhibited in the last 120 s, using paired-samples t-tests. We again conducted these analyzes for all markets and fixation parameters. We report the degrees of freedom for all t-tests as t_{df}, with decimal values indicating adjusted degrees of freedom to account for deviations from sphericity. To assess the effects of a potential convergence of visual focus across and within periods, we calculated repeated-measures analyzes of variance as well as linear regression analyzes. In the next step, we employ Pearson's correlation coefficient to analyze associations between traders' personal characteristics, their fixation count, duration, and frequency on the most relevant areas of interest, as well as their trading performance. Lastly, we computed mediation-analyzes between traders' personal characteristics and their trade performance, with the fixation parameters acting as mediators (see Figure OAF23 in the Online Appendix).

6. Results

6.1. Visual focus and element selection

First, we want to focus on visual focus within an asset market design. For visual focus, in Fig. 3, we present the results of the mean differences (md) and report t-test results for relative fixation count on the different information elements in CPL and LTD (upper left figure) of the SSW markets as well as the PS markets (lower left figure). Our results remain robust whether we rely on fixation duration or frequency (see Figure OAF12 in the Online Appendix).

For both standard trading interfaces (CPL) of the SSW and PS markets, we find that the order submission field receives the most visual focus, making up approximately 45% of the fixations. This is not surprising, given its central position and role as an input field for limit and market orders. For both limited trading interfaces (LTD) of the SSW and PS markets, the percentage of visual fixations on the order submission field increases by 10 percentage points to 55% of the visual focus.

Among the information elements, the order book receives the most visual focus, regardless of the underlying asset market design and the employed trading interface, attracting between 23% and 32% of all visual fixations. This result aligns with the findings of Teschner et al. (2015) who study the effects of a customizable trading interface on trading performance. Additionally, Teschner et al. (2015) report that the limit order book is the most frequently selected screen element (95%) before an order was submitted in a field study with 800 traders.

For the trading interfaces in the SSW markets, the order book is followed by the inventory field receiving 9% and the time clock field receiving 5% of visual focus. The signals field, the price chart, and the personal order history combined only constitute approximately 11% of visual focus throughout the whole experiment. For the trading interfaces in the PS markets, we find that the order book is followed by the signals and inventory fields (both slightly less than 10%). Considering these results, in particular, the limited visual focus on the chart is of interest as illustrative content can strongly attract humans' attention (Sanchez and Wiley, 2006).

In the LTD treatments of SSW and PS markets, we focus in more detail on information selection. Traders could choose three out of six information elements. Overall, traders opened information elements in 1046 of the 1080 possible instances in LTD of SSW (4 cohorts × 9 traders × 10 periods × 3 information elements = 1080). There were 15 traders out of 36 who opened fewer than three information elements in one or multiple periods during the course of the LTD of SSW. Similarly, traders opened information elements in 595 of the 600 possible instances in LTD of PS (4 cohorts, × 10 traders, × 5 periods, × 3 information elements, = 600). There was one trader out of 40 traders who opened only 2 information elements in all five periods during the course of the LTD of PS market.

The upper and lower right panels in Fig. 3 illustrate the mean selection rate for each information element. The mean selection rate expresses the average percentage of a particular information element being selected throughout the entire experiment. We find that traders opened the inventory field 263 out of 360 times in LTD of the SSW design, followed by the order book with 260 out of 360 times and the time clock with 190 out of 360 times (4 cohorts ×, 9 traders ×, 10 periods ×, 1 information element =, 360). The signals field, price chart, and personal order history are in the bottom half of the selected elements. The order of selected elements in LTD of the SSW market aligns with the order of visual focus in CPL of the SSW market, with the exception of the inventory field, as illustrated in Fig. 3. This implies that visual

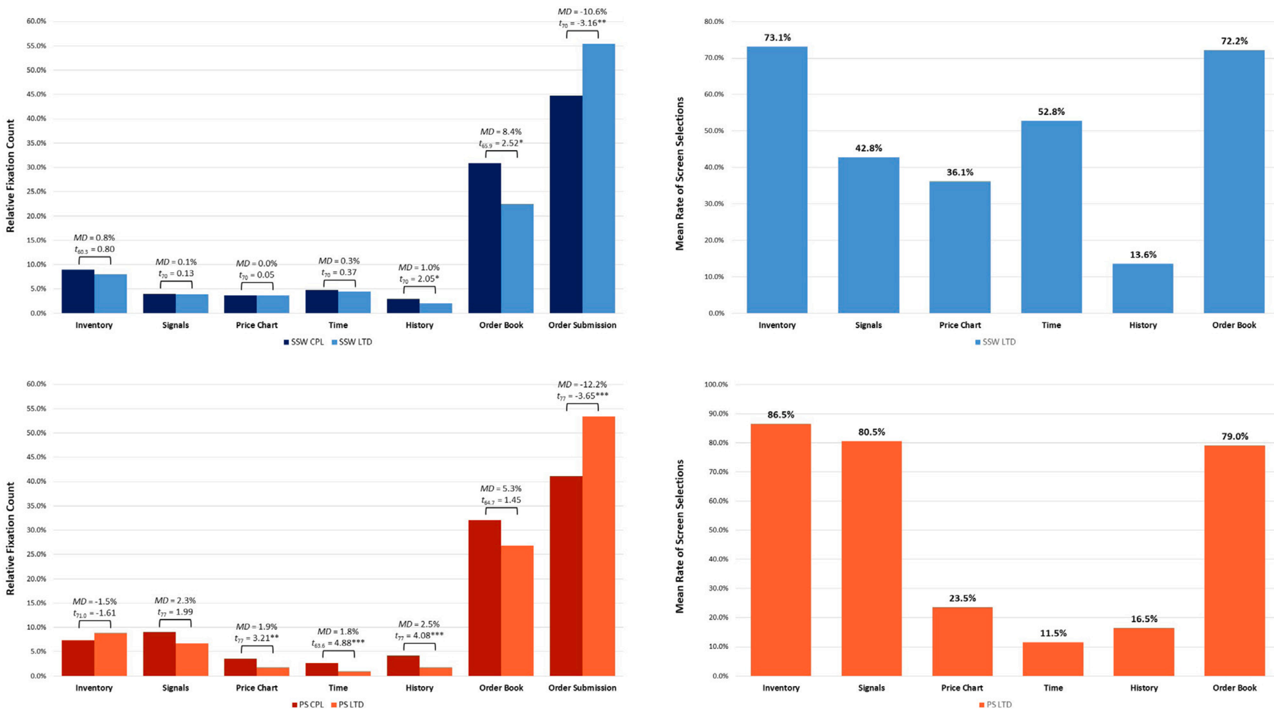

Fig. 3. Figure upper left: Mean differences (MD) and t-test results for fixation count between SSW CPL markets (dark blue bars, N = 36) and SSW LTD markets (light blue bars, N = 36). Figure lower left: Mean differences (MD) and t-test results for fixation count between PS CPL markets (dark red bars, N = 39) and PS LTD markets (light orange bars, N = 40). Figure upper right: The mean rate of screen selections in percentage in SSW LTD (light blue bars). Figure lower right: The mean rate of screen selections in percentage in PS LTD markets (light orange bars). The mean selection rate expresses the average percentage of a particular information element being selected throughout the whole experiment. (* p < .05, ** p < .01, *** p < .001).

fixations are, overall, a good proxy for the order of selection in the limited trading interface of the SSW market.

We find some notable differences between visual fixations and selection concerning the inventory field for the SSW market. The inventory field is the most frequently selected information element, but it receives little visual focus (9%) throughout the experiment. This implies that traders do not primarily focus on the inventory field although the majority deem it indispensable for trading. In contrast, traders fixate more often on the order book, although it is selected less frequently than the inventory field.

Similarly, we also find that traders' fixation counts on information elements recognized in CPL of the PS market largely correspond to the most frequently selected elements in the LTD of the PS market. The order book, signals table, and inventory field receive the most visual focus in CPL and are also the most frequently selected elements LTD. Traders opened the inventory field 173 out of 200 times in LTD of the PS design, followed by the signals table (160 out of 200 times), and the order book (158 out of 200 times). We want to re-highlight that the inventory field is the most frequently selected information element in LTD of the PS market, but it receives only limited visual focus (7%) throughout the CPL of the PS market. Given the high importance of private signals in the PS design, traders select the signals table even more often than the order book. This observation evidences a more stable selection pattern of traders in LTD of PS compared to SSW markets. This difference can be rationalized by the higher informational content provided in the signal table of PS. Traders in SSW seem to attribute less value to the dividend information and, therefore, may substitute this field with either the price chart or the time clock.

Based on these results, we accept Hypothesis 1 concluding that traders' visual fixations on information elements recognized in CPL of the SSW (or PS) market correspond to the most frequently selected elements in the LTD of the respective asset market design.

Second, we want to focus on visual focus among different asset market designs. We again calculate the mean differences (md) and t-test results for relative fixation counts on the different information elements in the CPL of SSW and PS markets (see Figure OAF14 in the Online Appendix for a graphical representation and test statistics). We find strong evidence that visual fixations on information elements differ between the SSW and the PS markets with regard to four out of the six information elements. According to the fixation count parameter, traders in SSW markets have a significantly stronger visual focus on the time clock in SSW than in PS, implying that traders may be more worried about the remaining time in a bubble-prone setting compared to an information aggregation setting. In contrast, traders in PS markets have a stronger visual focus on the signals field. This observation is plausible, given that traders focus more on the signals field if it features private rather than public information. The results for the time clock and signals table remain robust if we rely on fixation duration or frequency (see Figure OAF14 in the Online Appendix). We also find some weak evidence for differences in visual focus regarding the personal order history and the inventory field. These results, however, are not robust across the different fixation measures and should be interpreted cautiously.

We also find that the mean selection for the time clock is significantly higher in the LTD of SSW compared to LTD of PS, again underlining traders' preference for the time clock in SSW markets (see Figure OAF16 in the Online Appendix). Similarly, the mean selection for the signals field is significantly lower in the LTD of SSW compared to LTD of PS, which shows that traders select the signals field more frequently if it features private rather than public information. As we did not pre-register the hypothesis that the selection rate differs between the asset market designs, we will treat our observations as tentative results at this point.

Based on these results, we accept Hypothesis 2 concluding that the importance of information elements to a trader indeed differs between the SSW bubble market setting and the PS information aggregation setting.

Third, we investigate the relationship between traders' personal characteristics and fixation count (see also section 2.1.3 in the Online

Table 3
Pearson's Correlations between the fixation count on different areas of interest and personal characteristics (Cognitive Reflection (CRT), Fluid Intelligence (APM), Financial Literacy Score (FLS), Social Value Orientation (SVO)). The abbreviations for the information elements are as follows:
IV - Inventory Field SG - Signals Field PC - Price Chart
TM - Time Clock HS - Personal Order History OB - Order Book
OS - Order Submission.

SSW CPL	CRT N = 20	APM N = 36	FLS N = 36	SVO N = 36	SSW LTD	CRT N = 25	APM N = 36	FLS N = 36	SVO N = 36
IV	0.06	0.10	0.04	0.02	IV	−0.40*	−0.35*	−0.02	−0.23
SG	0.13	−0.02	0.03	−0.22	SG	0.32	0.13	0.29	0.11
PC	−0.12	−0.38*	−0.18	−0.11	PC	−0.03	0.00	−0.20	0.26
TM	−0.17	−0.20	−0.08	−0.18	TM	−0.07	0.16	0.15	0.09
HS	0.13	−0.07	−0.10	−0.16	HS	−0.19	0.07	−0.05	0.27
OB	−0.11	0.01	−0.12	0.08	OB	0.61**	0.10	0.32	−0.27
OS	0.09	0.10	0.15	0.06	OS	−0.50*	−0.06	−0.36*	0.21
PS CPL	**CRT N = 27**	**APM N = 39**	**FLS N = 39**	**SVO N = 39**	**PS LTD**	**CRT N = 40**	**APM N = 40**	**FLS N = 40**	**SVO N = 40**
IV	−0.20	0.11	−0.35*	0.17	IV	−0.09	−0.35*	−0.31	−0.04
SG	0.29	0.21	0.32*	−0.05	SG	0.39*	0.20	0.31	0.10
PC	−0.04	0.00	−0.19	−0.25	PC	−0.06	−0.01	−0.24	0.05
TM	0.06	−0.03	0.21	−0.24	TM	−0.17	0.17	0.27	−0.25
HS	−0.04	−0.23	0.06	−0.18	HS	−0.35*	−0.12	−0.25	−0.12
OB	0.03	0.46**	−0.04	0.03	OB	0.02	0.05	−0.04	0.02
OS	−0.11	−0.50**	−0.01	0.06	OS	−0.03	0.00	0.11	−0.01

* p < .05, ** p < .01, *** p < .001.

Appendix for a table of descriptive statistics and histograms). Table 3 contains the correlations between fixation count on information elements and personal characteristics. In CPL of the SSW design, we find some weak evidence that the correlation between APM and the fixation count on the price chart is negative, implying that high fluid intelligence is negatively correlated with visual focus on the price chart. However, we find that the negative correlation between APM and the price chart no longer remains significant if we rely on fixation duration or fixation frequency (see Tables OAT4 and OAT5 in the Online Appendix). In regard to LTD of the SSW design, Table 3 also shows that there is a significant positive correlation between traders with high scores in the cognitive reflection task (CRT) and fixation count on the order book, while there is a significant negative correlation between traders with high CRT and fixation count on the order submission. The results remain robust if we measure fixations based on duration and frequency (see Tables OAT4 and OAT5 in the Online Appendix).

Considering CPL of the PS design, we find a positive correlation between traders with APM and fixation count on the order book, while there is a significant negative correlation between traders with high APM and fixation count on the order submission field. This aligns with the results of Corgnet et al. (2018), who also find that high fluid intelligence provides traders with computational skills and engages in abstract reasoning, which are necessary to draw a statistical inference based on available signals and thereby learn the true value of the asset. Traders with high fluid intelligence focus more on the order book, which includes all available offers, rather than just the order submission field that contains the best ask and best bid. We also find that a higher financial literacy score (FLS) has a positively significant correlation with the fixation count on the signals field; however, this result is only significant at the 5% level. We find the same positively significant correlation with fixation frequency on the signals field, but not with fixation duration (see Tables OAT4 and OAT5 in the Online Appendix). The coefficient of (FLS) is no longer statistically significant in LTD of the PS design.

Table 4 displays Pearson's correlations between selected information elements and traders' personal characteristics in LTD of SSW and PS markets. We find that the correlations between personal characteristics and selected information elements partially align with the findings from the eye fixation table. In SSW LTD, the positive correlation between traders with high scores in the cognitive reflection task (CRT) and the selection of the order book is significant. We also find some weak evidence that the correlation of APM and selecting the inventory field is negative, implying that high fluid intelligence is negatively correlated with selecting the inventory field. In PS LTD, we observe a negative correlation between traders' scores in the CRT (or FLS, respectively) and the selection of personal order history.

Table 4
Pearson's Correlations between the selected information elements and personal characteristics (Cognitive Reflection (CRT), Fluid Intelligence (APM), Financial Literacy Score (FLS), Social Value Orientation (SVO)). The abbreviations for the information elements are as follows:
IV- Inventory Field SG - Signals Field PC - Price Chart
TM - Time Clock HS - Personal Order History OB - Order Book.

SSW LTD	CRT N = 25	APM N = 36	FLS N = 36	SVO N = 36
IV	−0.37	−0.37*	0.03	−0.17
SG	0.16	0.00	0.19	0.11
PC	0.13	0.12	−0.12	0.25
TM	−0.10	0.14	0.10	0.08
HS	−0.23	0.16	−0.01	0.18
OB	0.40*	−0.08	0.05	−0.37
PS LTD	**CRT N = 40**	**APM N = 40**	**FLS N = 40**	**SVO N = 40**
IV	0.05	−0.13	0.03	0.06
SG	0.30	0 .16	0.33*	−0.04
PC	−0.04	−0.03	−0.25	0 .00
TM	−0.13	0.25	0.26	−0.21
HS	−0.39*	−0.25	−0.42**	−0.06
OB	0.20	0.15	0.26	0.08

* p < .05, ** p < .01, *** p < .001.

To sum up, our evidence on the relationship between personal characteristics and visual focus is mixed. We observe that individuals with strong cognitive skills may exhibit a positive correlation with the order book but a negative correlation with the price chart in bubble prone settings, while traders with higher cognitive skills or a higher financial literacy score may focus more on the signals table and less on their personal order history in information aggregation settings.

Based on these results, we accept Hypothesis 3 for traders in the SSW and PS design. Traders' visual focus on information elements correlates with personal characteristics. Still, we believe that further research is warranted to gain a deeper understanding of these complex relationships.

We also analyze gender differences in regard to fixation measures and information elements, however, we find no conclusive evidence. In

CPL of the SSW design, there are no differences between male and female traders for all three fixation measures on a significant level. In CPL of the PS design, we find that male traders' fixation count, duration, and frequency are lower on the inventory table compared to female traders. Furthermore, male traders' fixation count and frequency are higher on the signals table compared to female traders at the 5% level (see Tables OAT6 and OAT8 in the Online Appendix). In LTD of the PS design, we find that male traders' fixation count and frequency are lower on the personal order history field compared to female traders at the 5% level (see Tables OAT6, OAT7, and OAT8).

6.2. Time trends in visual focus and element selection

This section investigates whether traders' visual focus and information selection evolve over time, as outlined in Hypotheses 4 to 6. While the underlying questions are theoretically relevant, the empirical evidence is largely inconclusive. Therefore, we limit our discussion to the most salient patterns and restrict detailed statistical reporting to the Online Appendix (see Tables OAT12OAT16).

Fig. 4 displays the mean fixation counts and selection rates across periods for the SSW and PS designs. For the SSW design, visual focus appears unstable across periods. In the SSW CPL markets, we observe a decreasing trend in visual focus on the order submission field, accompanied by a slight increase in fixations on the order book. Additionally, the importance of the time clock increases around period 7, suggesting a heightened awareness of the remaining time as the experiment progresses. In the corresponding LTD markets, the order book and inventory fields are most frequently selected, although the selection of the inventory field decreases modestly over time. In contrast, the selection rate for the time clock increases from 30% to 60%.

For the PS design, importance patterns appear to be more stable across periods. The order submission field consistently receives the highest number of fixations, followed by the order book, inventory field, and signals table. In the limited interface condition, the inventory field, signals table, and order book are the most frequently selected, while other elements remain less relevant. These results point to overall greater temporal stability in the PS setting compared to the SSW.

To quantify convergence in visual focus, we compute a convergence parameter based on the absolute change in fixation counts between adjacent periods. The corresponding regression results are presented in the Online Appendix (Table OAT12). Across all treatments, we find no significant time trend in the convergence parameter, nor any meaningful effect of personal characteristics such as fluid intelligence (APM), financial literacy (FLS), or social value orientation (SVO). While we detect a slight convergence in fixation patterns on the price chart in SSW CPL, the effect is limited (see Table OAT13). Based on these findings, we reject Hypotheses 4 and 5.

Fig. 5 displays intra-period fixation patterns across four 30-second intervals. Here, we identify consistent shifts in visual focus from static to dynamic information elements within each trading period, in line with Hypothesis 6. For both market designs, traders focus more on the signals table at the beginning of a period and shift their focus toward the order book and time clock as the period progresses. Repeated-measures ANOVAs confirm these patterns, with significant interaction effects for key elements such as the price chart, signals table, order submission field, and time clock across both interface conditions. Based on these results, we accept Hypothesis 6 for traders in both asset market designs. Traders' visual focus will transition from static to dynamic trading screen elements during the market period.

Taken together, while we find little support for convergence in attentional patterns across periods or effects of personal characteristics, our intra-period analysis provides robust evidence of dynamic adjustments in visual focus. Traders increasingly prioritize elements that update in real time, suggesting a context-sensitive allocation of focus during the decision-making process.

6.3. Attention in the last mile of trading: Operational and informational aspects

Besides examining the visual focus throughout the experiment, we also explore the relationship between visual focus and decision-making in asset markets. To this end, we investigate which information elements traders consider before making trading decisions (submitting limit orders, market orders, or canceling a limit order). In the Online Appendix, we also separate trading decisions into limit orders, market orders, and canceling orders, and we find very similar fixation patterns (see Tables OAT9, OAT10, and OAT11).

This analysis captures the operational dimension of attention, i.e., the 'last mile' immediately preceding order submission. The consistent inclusion of the order book among the final three fixations highlights its importance for execution-related focus. Yet, the broader attention patterns observed throughout trading periods are equally revealing. Earlier fixations reflect information search, market monitoring, and expectation formation, which provide the groundwork for efficient execution. The overlap between these stages suggests that informational and operational attention is intertwined rather than distinct. The order book thus serves both as an information source and as a practical interface for acting upon that information. This integrated perspective explains why we analyze not only the last-fixation sequences but also the entire time allocation of visual attention across market phases.

Table 5 illustrates the most frequent combinations of the last three fixations before traders submit limit orders, market orders, or cancel a limit order in the four treatments. We find that the seven most frequent combinations of the last three fixations contain the order submission field and/or the order book, accounting for almost 70% of observations in the CPL and LTD SSW markets. Note that a fixation is only counted if an item is fixated for at least 100 ms. It is therefore possible to submit an order without having fixed the order submission last. This is, e.g., the case if a trader has already entered a price (and an order size) before and then only pushes the submit button. This could be done in under 100 ms. The 8th (or 7th, respectively) most frequent combination consists of three subsequent fixations on the inventory field. We want to highlight that traders, on average, do not particularly focus on the price chart before submitting or canceling an order. In fact, out of the 991 observed last three fixations, only 33 contain the price chart (0.3%) in SSW CPL market, implying that past prices do not seem to have a significant impact before traders make an investment decision.

Similarly, we find that the six most frequent combinations of the last three fixations only contain the order submission field and/or the order book and account for almost 65% of observations in the PS CPL market (and 72% of observations in the PS LTD market). In the PS CPL market, the seventh most frequent combination consists of three subsequent fixations on the signals field, implying that traders focus more on the signals field before submitting a trading offer if it features private information rather than public information. We again find that traders, on average, do not fixate on the price chart before submitting or canceling an order. Out of 1155 observed last three fixations, only 34 contain the price chart (0.3%) in our PS CPL market design.

Overall, we find that three subsequent fixations on the order book are the second most common combination before trading decisions are made in both, the SSW CPL markets and PS CPL markets. The three subsequent fixations on the order book may imply that some traders do not submit their orders immediately but rather first input the orders and then wait for the right opportunity to submit them. Some traders may be aware that they signal the content of their information to others via trading and hence, prefer to conceal their information.

To further explore whether the observed attention patterns reflect operational necessity or a broader informational focus, we conducted a supplementary analysis distinguishing between market and limit orders. Market orders, characterized by time pressure and execution urgency, contrast with limit orders, which allow for greater discretion in timing. The results, presented in the Online Appendix Tables OAT9

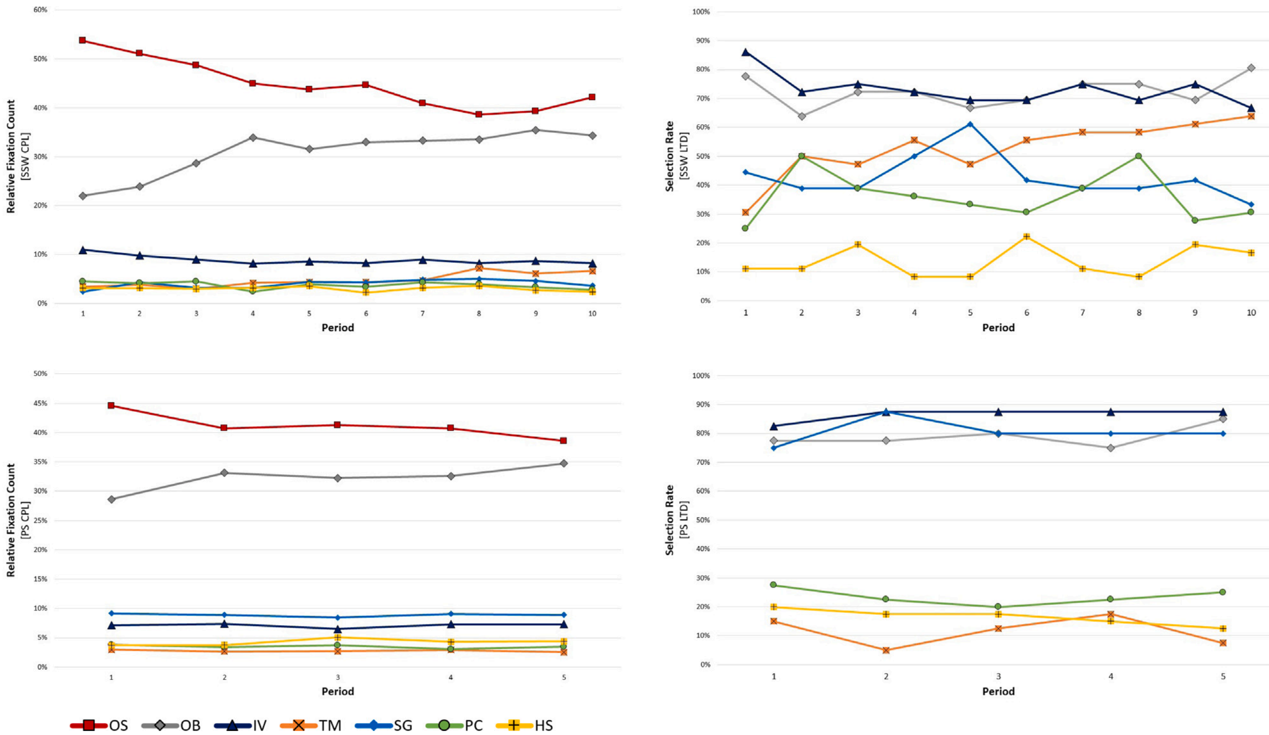

Fig. 4. The mean selection rate expresses the percentage of a particular information element being selected in a given period. Two upper figures: Mean fixation count (left) and selection rate (right) for SSW markets. Two bottom figures: Mean fixation count (left) and selection rate (right) for PS markets.

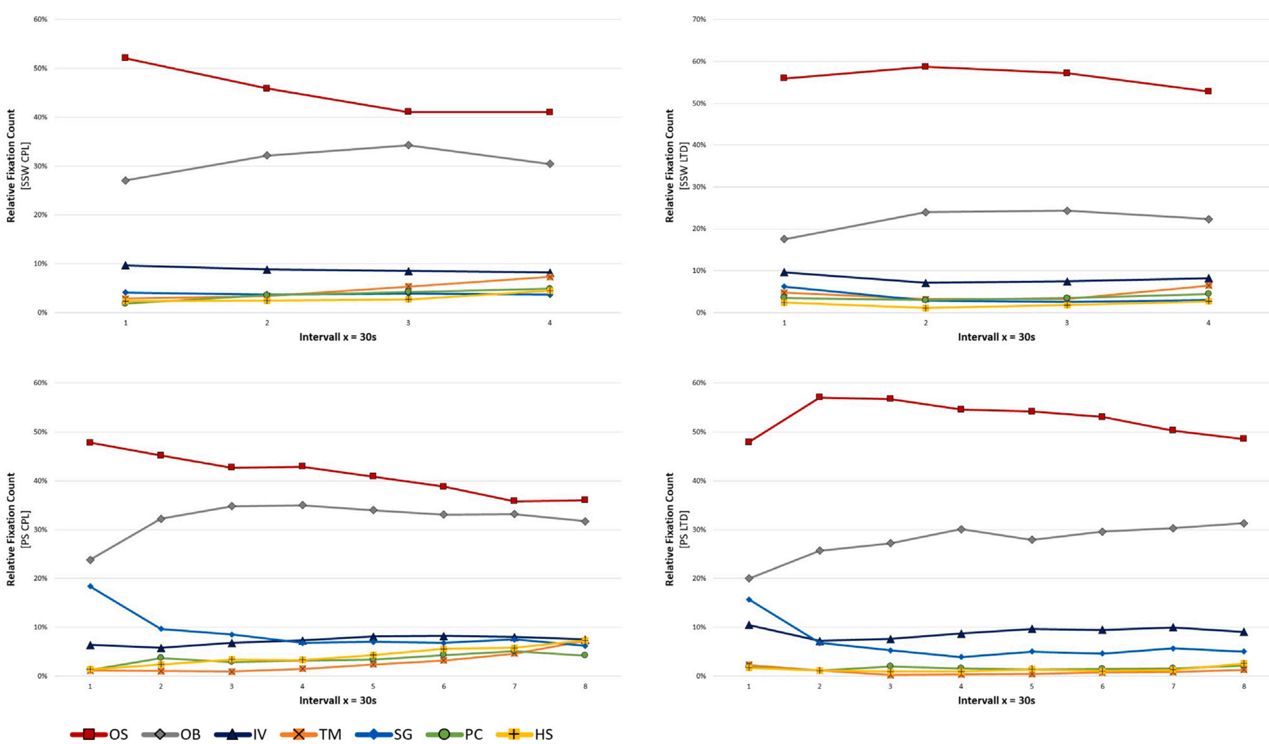

Fig. 5. Intra-period mean fixation counts per 30-second interval. Upper row: SSW markets; Lower row: PS markets.

(limit orders) and OAT10 (market orders), reveal no significant differences in the distribution of the last three fixations between these order types. The order book appears as part of the final fixation sequence in both contexts, suggesting that the observed attention is not merely a mechanical response to execution pressure but reflects a stable and general focus on the order book's informational content.

Next, Table 6 illustrates combinations of the last three unique fixations before making a trading decision; hence, we exclude subsequent fixations on an identical information element. In CPL of the SSW markets, we find that the eight most frequent combinations of the last three unique fixations contain the order book and account for almost 50% of observations. Furthermore, we find that the inventory field appears in

Table 5
Most frequent combinations of last three fixations before trading decisions (aggregation of limit, market, canceling orders) in the SSW and PS markets. The fixations are represented by descending order: The third last fixation is the abbreviation on the left, the second last is the abbreviation in the middle, and the last fixation is the abbreviation on the right. The abbreviations for the information elements are as follows:
IV - Inventory Field   SG - Signals Field   PC - Price Chart
TM - Time Clock   HS - Personal Order History   OB - Order Book
OS - Order Submission.

SSW CPL	Perc.	Accum. Perc.	SSW LTD	Perc.	Accum. Perc.
OS-OS-OS	24.6%	24.6%	OS-OS-OS	43.2%	43.2%
OB-OB-OB	18.4%	43.0%	OB-OB-OB	15.8%	59.0%
OS-OS-OB	7.7%	50.7%	OB-OS-OS	4.8%	63.8%
OB-OB-OS	5.1%	55.8%	OS-OS-OB	3.6%	67.5%
OS-OB-OS	4.8%	60.6%	OB-OB-OS	3.1%	70.5%
OS-OB-OB	4.1%	64.8%	OS-OB-OB	3.1%	73.6%
OB-OS-OS	4.0%	68.8%	IV-IV-IV	2.4%	76.0%
IV-IV-IV	2.7%	71.5%	IV-OS-OS	1.6%	77.6%
PS CPL	Perc.	Accum. Perc.	PS LTD	Perc.	Accum. Perc.
OS-OS-OS	26.1%	26.1%	OS-OS-OS	45.0%	45.0%
OB-OB-OB	15.8%	41.9%	OB-OB-OB	10.0%	55.0%
OS-OB-OB	6.7%	48.6%	OS-OS-OB	5.0%	60.1%
OS-OS-OB	6.3%	54.9%	OS-OB-OB	4.6%	64.7%
OB-OS-OS	5.4%	60.3%	OB-OB-OS	3.7%	68.4%
OB-OB-OS	4.9%	65.2%	OB-OS-OS	3.7%	72.1%
SG-SG-SG	2.6%	67.8%	IV-IV-IV	2.8%	74.9%
IV-IV-IV	2.5%	70.3%	OS-OS-IV	2.6%	77.5%

the three most frequent combinations of the last three unique fixations, while the price chart and the personal order history do not appear in the eight most frequent combinations of the last three unique fixations. For CPL of the PS markets, we want to re-highlight that the eight most frequent combinations of the last three unique fixations contain the order book and account for almost 50% of observations. In LTD of the SSW and PS markets, we also find that traders focus in particular on the order book and inventory fields. In contrast, the price chart receives comparatively less attention. We want to re-highlight that we enable traders to cancel their own orders in the order book because we want to guarantee a high degree of flexibility in regard to customizing trading decisions. In the Online Appendix, we therefore also analyze the last three fixations, sorted according to limit orders, market orders, and canceling orders. We find similar fixation patterns as in Tables 5 and 6.

On the basis of these results, we accept Hypothesis 7 for the order book. The order book receives more visual focus than non-market tracking elements before traders make buying or selling decisions.

Finally, we want to assess whether the visual focus on certain trading elements impacts trading performance. In Table 7, we outline Pearson's correlations between fixation counts on different areas of interest and trader performance. We find similar results for fixation duration and fixation frequency in the Online Appendix (see Tables OAT20 and OAT21). We quantify traders' performance by the total amount of taler they earn throughout the asset market experiment. In PS, trader performance depends on the cumulative earnings across the five periods. In SSW, trader performance depends on the final cash balance in the last period.

For the CPL of SSW, the results reveal that a stronger focus on the order book correlates positively with performance, while a stronger focus on the order submission box correlates negatively. The positive correlation between the order book and trade performance remains significant at the 5% level if we rely on fixation duration or fixation frequency (see Table OAT20 in the Online Appendix). The negative correlation between order submission and trade performance remains significant at the 5% level in the case of fixation duration but is no longer significant in the case of fixation frequency (see Figure OAT21 in the Online Appendix). For LTD of SSW, we find no significant correlations between fixation counts on information elements and trading performance.

For the CPL of PS, we find a positive correlation between trading performance and personal order history at the 5% level. This positive correlation between personal order history and trade performance remains significant at the 5% level if we rely on fixation duration or fixation frequency (see Tables OAT20 and OAT21 in the Online Appendix). For the LTD of PS, we find a positive correlation between trading performance and the signals table at the 1% level (remaining robust in the cases of fixation duration and frequency) (see Tables OAT20 and OAT21 in the Online Appendix). However, the negative correlation between trading performance and personal order history does not remain robust in the cases of fixation duration and frequency.

We also outline Pearson's correlations between selected information elements and trader performance. The statistically significant results reported in this table largely align with the significant correlations between fixation counts on information elements and trading performance. For the LTD of PS, the positive correlation between trading performance and the signals table remains significant at the 1% level. The negative correlation between trading performance and personal order history also remains significant.

In light of these results, we support Hypothesis 8 for both the SSW and PS designs, suggesting that traders' visual focus on information elements does indeed correlate with their trading performance. Still, we believe that further research is warranted to gain a deeper understanding of these complex relationships.

7. Conclusion and outlook

In this paper, we study traders' visual focus on and the selection of information elements by employing eye-tracking in laboratory experimental asset markets. Thereby, we explore which information elements receive the most visual focus during visual processing and whether visual focus corresponds with the active selection of screen elements. Furthermore, we assess which factors influence the visual focus on and selection of screen elements, whether there are time trends, and ultimately, how focus relates to trading decisions and performance.

Regarding the information elements available to traders, our data indicates that the' most important element for traders is the order book, constituting between 23% and 32% of all visual fixations. Contrary

Table 6

Most frequent combinations of last three unique fixations before trading decisions (aggregation of limit, market, canceling orders) in the SSW and PS markets. The fixations are represented by descending order: The third last fixation is the abbreviation on the left, the second last is the abbreviation in the middle, and the last fixation is the abbreviation on the right. The abbreviations for the information elements are as follows:
IV - Inventory Field SG - Signals Field PC - Price Chart
TM - Time Clock HS - Personal Order History OB - Order Book
OS - Order Submission.

SSW CPL	Perc.	Accum. Perc.	SSW LTD	Perc.	Accum. Perc.
IV-OS-OB	10.1%	10.1%	OB-IV-OS	6.1%	6.1%
IV-OB-OS	9.9%	20.0%	IV-TM-OS	5.9%	12.1%
OB-IV-OS	6.3%	26.2%	IV-OB-OS	5.7%	17.7%
SG-OB-OS	5.7%	31.9%	IV-OS-OB	5.6%	23.3%
SG-OS-OB	5.0%	36.9%	TM-OB-OS	5.2%	28.6%
TM-OB-OS	4.9%	41.9%	OB-OS	4.3%	32.9%
TM-OS-OB	4.6%	46.5%	PC-OS-OB	4.0%	36.9%
OB-OS	3.6%	50.2%	SG-OB-OS	3.8%	40.6%
PS CPL	**Perc.**	**Accum. Perc.**	**PS LTD**	**Perc.**	**Accum. Perc.**
IV-OS-OB	13.1%	13.1%	IV-OB-OS	13.7%	13.7%
IV-OB-OS	12.8%	25.9%	IV-OS-OB	10.1%	23.8%
SG-OB-OS	5.3%	31.2%	OB-IV-OS	7.5%	31.2%
OB-IV-OS	5.1%	36.3%	IV-OS	6.2%	37.4%
SG-OS-OB	4.6%	40.9%	SG-OB-OS	6.0%	43.4%
PC-OB-OS	3.7%	44.6%	OB-OS	5.2%	48.6%
PC-OS-OB	3.3%	47.9%	IV-OS-OB	4.8%	53.4%
OS-IV-OB	3.3%	51.2%	IV-PC-OS	3.4%	56.7%

Table 7

First four columns to the left: Pearson's Correlations between the fixation counts on different areas of interest and trade performance (TP) for traders in CPL and LTD of the SSW and PS design. Last two columns to the right: Pearson's Correlations between the selected information elements and trade performance (TP) for traders in LTD of the SSW and PS design. The abbreviations for the information elements are as follows:
IV - Inventory Field SG - Signals Field PC - Price Chart
TM - Time Clock HS - Personal Order History OB - Order Book
OS - Order Submission.

	Fixation counts & TP				Selected elements & TP	
	SSW CPL	SSW LTD	PS CPL	PS LTD	SSW LTD	PS LTD
IV	−0.33*	−0.11	−0.15	−0.13	−0.08	0.00
SG	0.19	0.20	0.19	0.53***	−0.01	0.51***
PC	−0.06	0.18	0.02	−0.22	0.23	−0.28
TM	0.05	0.14	0.05	0.02	−0.08	−0.07
HS	0.21	0.11	0.34*	−0.35*	0.03	−0.54*
OB	0.41*	0.11	−0.09	0.20	−0.10	0.36*
OS	−0.36*	−0.21	−0.03	−0.26	–	–
N	36	36	39	40	36	40

* p < .05, ** p < .01, *** p < .001.

to our expectations, we find that the price chart is neither frequently chosen nor does it attract substantial visual focus, even in markets prone to bubbles. In contrast to Bose et al. (2022), our results suggest that when traders can access multiple sources of information, the price chart does not emerge as a critical determinant of decision-making. Moreover, traders devote little attention to the price chart immediately before placing or accepting orders.

This finding is noteworthy because visual content typically attracts attention (Sanchez and Wiley, 2006), and market traders pursuing technical analysis assume that past prices contain valuable information for future price developments. A plausible explanation for the observed result lies in the structure of our experimental asset markets: the asset's fundamental value is largely transparent – deterministic in the SSW design and assuming one of three known values in the PS design – which reduces a potential informational benefit of tracking historical prices. In real markets, however, fundamental values are more uncertain, and price charts usually incorporate, due to a higher number of market traders and transactions, far richer information, and cover extended time horizons. An additional behavioral dimension we cannot cover in our experiment is the specific design of information elements, such as the price graph. Bazley et al. (2021), for example, show the pervasive effects of coloring elements, which is often the case for charts in practice. Furthermore, while price charts are inherently backward-looking, the order book offers forward-looking cues about market liquidity and potential price movements. The two market designs in our study, therefore, incentivize trading on fundamentals rather than on patterns in historical data, making the application of technical analysis difficult given the limited historical trading data and the restricted number of input variables.

Further, our data reveal that the order of selected information elements largely aligns with the order of visual focus (see Fig. 3), implying that eye-tracking is a reasonable proxy for the set of actively selected elements in the limited trading interface (Glaholt et al., 2009). As active selection should more strongly relate to top-down goal-driven attentional processes, whereas visual focus could also be shaped by bottom-up stimulus-driven processes, this overlap indicates that the latter are largely overwritten in situations with a strong task focus (Kowler, 2011), supporting theories of rational inattention (Sims, 2010). Thus, in such contexts, between-subject (Engelmann et al., 2021) visual focus should also be a reasonable proxy for top-down attention. Finally, we document that cognitive capabilities correlate with the attention attributed to certain screen elements as well as trading performance (see Tables 3 and 7). However, it is important to note that generalizing these statements about correlations is hardly possible as they vary conditionally based on the specific information element used and the underlying asset market design Therefore, we suggest future studies replicate our approach in real-world settings.

Our findings may serve as valuable information for practitioners who can learn about the processing of informative signals. We find that the most frequent combinations of the last three fixations before trading decisions consist of only two information elements, i.e., the order submission field and the order book (see Tables 5 and 6). Our results also reveal that a stronger focus on the order book correlates positively with trading performance in a bubble market setting, while a stronger focus on the order submission field correlates negatively (see Table 7). Although the order book fulfills a clear operational role, our findings indicate that traders attend to it not merely to execute, but also to extract information about market conditions. Given that informational and operational motives are inherently interwoven, our study contributes to the understanding of how these dual functions jointly shape attention and behavior in financial markets. The robustness of this pattern across order types (see Tables OAT9 and OAT10 of the Online Appendix) reinforces this interpretation. Even under high time pressure, traders exhibit a similar visual focus as in settings with greater temporal flexibility. This consistency indicates that attention to the order book cannot be explained solely by execution necessity but rather reflects its enduring informational role in guiding market actions and decisions. This integrative perspective extends the information-acquisition literature by highlighting the continuous interplay between information processing and action preparation in trading environments

Market inefficiencies related to selective attention and salience may be reduced if trading platforms make the order book more salient in their default settings. Furthermore, we find that traders with low APM scores pay more attention to the price chart in a bubble market setting. By hiding or decreasing the size of the price chart, and overall matching the relevance of a particular element with its visual salience, trading platforms may enable their users to achieve better trading returns and may contribute to the stabilization of the financial system by reducing bubble-and-crash tendencies (cf. Mosenhauer, 2023, who derives a similar suggestion).

In addition to these practical implications, we believe that our study delivers important academic evidence regarding the customization of trading interfaces in laboratory asset markets. We find that the price chart is neither frequently selected nor does it receive a lot of visual focus. So far, several experimental asset market studies have placed a significant emphasis on price graphs, sometimes covering roughly half (Fink et al., 2023; Giamattei et al., 2020; Razen and Kupfer, 2023) or up to a third of the trading interface (Hoyer et al., 2023; Huber and Rose, 2019; Huber et al., 2019; Lambrecht et al., 2024; Weitzel et al., 2020), while the time clock is positioned in the upper right corner, easily overlooked. Future asset market studies may adapt their trading interfaces accordingly.

In our design, we analyze the six most commonly featured information elements. In reality, investors may customize their trading interface according to their needs (Beunza and Stark, 2004). However, our scope is not to make predictions about the optimal amount, positioning, or visualization of information elements to improve trading performance. Future research could extend our current design and, for example, assess the willingness to pay for gaining access to more information elements or whether salient signals can influence trading behavior. Furthermore, we enable traders to cancel their own orders in the order book because we want to guarantee a high degree of flexibility regarding trading decisions. It might be interesting to assess whether the visual focus on the order book would decrease if traders cannot use the order book to cancel their own trades but use it exclusively as an information element.

CRediT authorship contribution statement

Matthias Herrmann-Romero: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Simon Liegl:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Martin Angerer:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Thomas Stöckl:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Methodology, Investigation, Conceptualization.

Ethical approval

The experimental design and procedures of the experiment were approved by the University hosting the lab before conducting the experiments. No harmful interventions or procedures were used in the study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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