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Commentary/Position Paper

Integrating health geography and behavioral economic principles to strengthen context-specific behavior change interventions

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Abstract

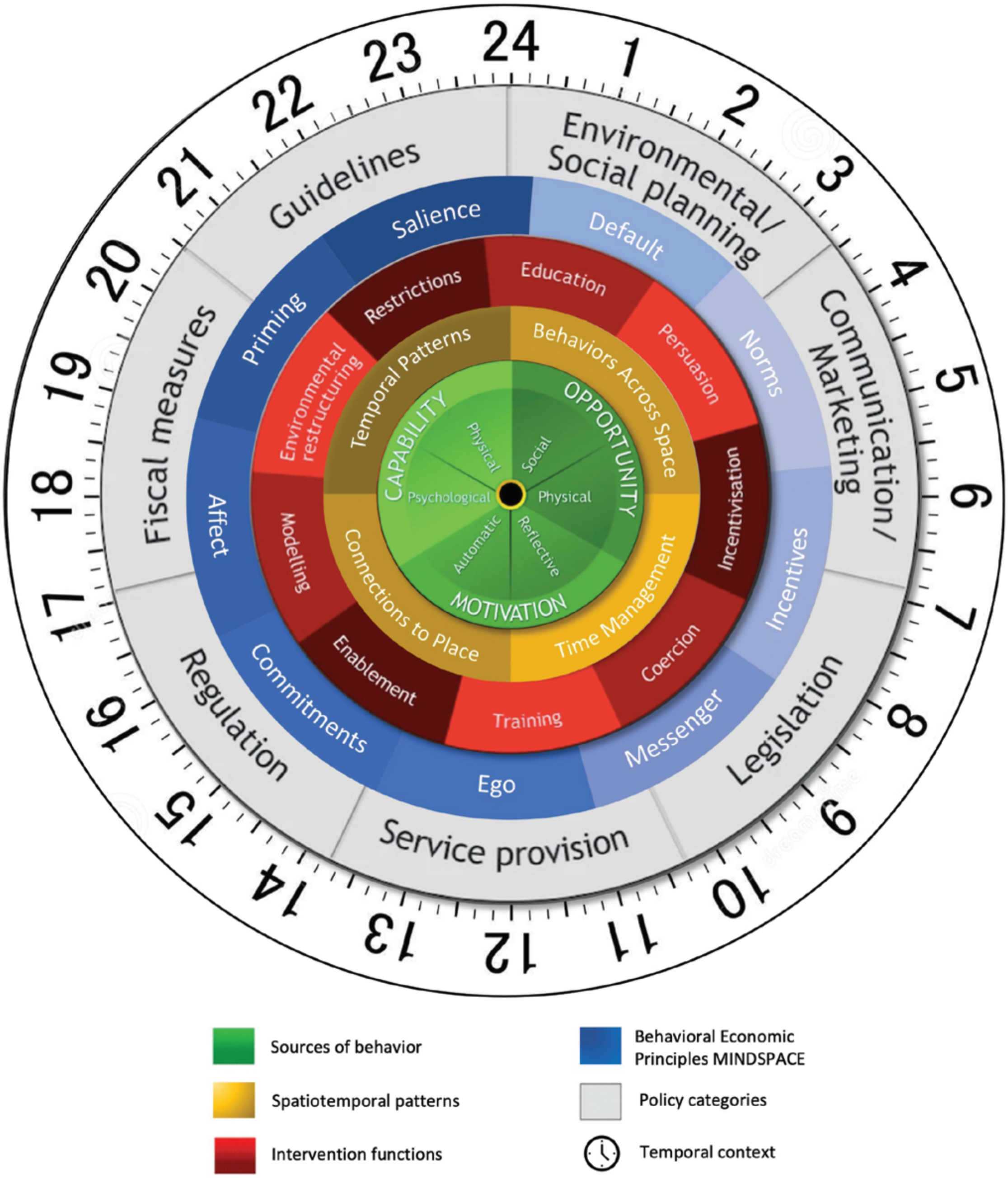
The long-term economic viability of modern health care systems is uncertain, in part due to costs of health care at the end of life and increasing health care utilization associated with an increasing population prevalence of multiple chronic diseases. Control of health care spending and sustaining delivery of health care services will require strategic investments in prevention to reduce the risk of disease and its complications over an individual's life course. Behavior change interventions aimed at reducing a range of harmful and risky health-related behaviors including smoking, physical inactivity, excess alcohol consumption, and excess weight, are one approach that has proven effective at reducing risk and preventing chronic disease. However, large-scale efforts to reduce population-level chronic diseases are challenging and have not been very successful at reducing the burden of chronic diseases. A new approach is required to identify when, where, and how to intervene to disrupt patterns of behavior associated with high-risk factors using context-specific interventions that can be scaled. This paper introduces the need to integrate theoretical and methodological principles of health geography and behavioral economics as opportunities to strengthen behavior change interventions for the prevention of chronic diseases. We discuss how health geography and behavioral economics can be applied to expand existing behavior change frameworks and how behavior change interventions can be strengthened by characterizing contexts of time and activity space.

Lay summary

Behavior change interventions are challenged by lack of information about the contexts influencing decisions patients make as part of their daily routine such as when, where, and how health behaviors occur. A new approach is required to strengthen behavior change interventions by integrating contexts of time and activity space so that strategies can be scaled across populations to influence how individuals make decisions about improving their health behaviors. Incorporating ideas from health geography and behavioral economics into the design of behavior change interventions provides an opportunity to collect and investigate individual-level health information characterizing contexts of individuals' activities across space, connections to place, time management, and patterns in behavior over time. By visualizing and characterizing key spatiotemporal contexts about an individual's day-to-day routine, insight can be gained about where and for how long activities occur and what opportunities exist for adapting day-to-day routines. This paper will discuss how theory from health geography could be applied to understand contexts influencing behaviors and how spatiotemporal information could be applied for the purpose of tailoring behavioral economic strategies to strengthen the design of behavior change interventions.

Keywords: behavior change interventions; health geography; behavioral economics; activity space; temporal patterns; prevention chronic disease

Graphical Abstract



Implications

Practice: Contexts influencing an individual's activity space are important for tailoring behavior change interventions so that clinic-based settings are generalizable to individuals' routine time-use patterns and contexts of location, timing, duration, and sequence of health-related behaviors.
Policy: A new approach is required to strengthen behavior change interventions by integrating contexts of time and activity space so that strategies can be scaled across populations to influence how individuals make decisions about improving their health behaviors.
Research: Future research should be aimed at integrating multidisciplinary theory and methods, health geography, and behavioral economics, with technology-based strategies to improve information about individual-level contexts of health behaviors in real-time and across different contexts.

Introduction

Day-to-day routine is a major determinant of patterns in health behaviors that influence health outcomes over time. Forming stable everyday routines is important for structuring daily tasks and responsibilities, achieving activities for physical functioning like eating and sleeping, and maintaining habits for health and well-being like exercising or taking medication [1–4]. A stable routine can be supportive when day-to-day behaviors that improve health status become habitual (e.g. daily exercise, healthy diet), and detrimental when trying to break from a routine with well-established habits that pose a risk for disease (e.g. smoking, sedentary behavior) [5]. There are important contextual factors influencing how, when, and why patterns of behavior develop, such as the characteristics of environments that influence the timing, location, and decisions to engage in health promoting or inhibiting behaviors, many of which contribute to health outcomes such as chronic disease. Research exploring contexts influencing the timing, sequence, and duration of routine day-to-day activities and interventions that support individuals with adapting their routines is very limited [2].

Behavior change interventions are critical to modifying health-related behaviors linked to the development of risk factors for chronic diseases [6, 7]. For example, behavior change interventions are commonly aimed at preventing and reducing a range of harmful and risky health-related behaviors including smoking [8], physical inactivity [9, 10], excess alcohol consumption [11, 12], and excess weight [13]. As well as promoting health improving and protective behaviors including physical activity [14], healthy diet [15], and use of medication [16]. Behavior change techniques are the active components within behavior change interventions [17] and provide a standardized classification of intervention content given a specified behavior outcome [18, 19]. A range of behavior change interventions targeting common risky health-related behaviors have been extensively studied, such as physical activity and management of overweight or obesity, which we use in this commentary as examples for discussing behavior change techniques and applying concepts we present.

Behavior change techniques most frequently reported in digital and face-to-face behavior change interventions promoting physical activity for adults with overweight or obesity (n = 62 studies) include goal-setting behavior (n = 84), self-monitoring of behavior (n = 77), feedback on behavior (n = 50), problem-solving (n = 27), social support (n = 40), instruction on how to perform behavior (n = 38), prompts/cues (n = 36), self-monitoring of outcomes (n = 30), graded tasks (n = 29), and information about health consequences (n = 27) [20]. Knowing what behavior change techniques are effective in given contexts is important for replicating interventions tailored to where individuals live, work, and play. Ideally, these behavior change interventions would be upstream to prevent or identify and reduce disease risk factors at an early point in time across an individual's life course so that health resources contribute toward maximizing healthy lifespans and postpone the onset of chronic disease [21].

Large-scale efforts to lower rates of chronic diseases are challenging [22, 23] with few studies reporting behavior change intervention content and effective and cost-effective behavior change techniques [18, 24, 25]. Inconsistent reporting of behavior change intervention content means only weak conclusions can be drawn regarding the effectiveness [18] and cost-effectiveness [24] of behavior change techniques linked to target behaviors. For example, meta-analyses found there were no behavior change interventions with the same combination of behavior change techniques, including wide-ranging differences in pooled effect sizes of behavior change techniques within digital versus face-to-face interventions promoting physical activity in overweight or obese adults [20]. Furthermore, interventions commonly delivered in clinical settings do not identify how individuals can routinize intervention techniques within the contexts of their day-to-day schedules [26]. Responding to this challenge requires detailed information about health-related behaviors, including spatial and temporal contexts, so behavior change interventions are tailored to contexts outside of clinic-based settings where health behaviors occur. For example, social and physical environments play an important role in promoting or inhibiting health behaviors [27], including contexts that influence sequential patterns in the location, timing, and duration of routine behaviors. Assessing the unique spatiotemporal contexts of these behaviors is critical for tailoring behavior change interventions so that clinic-based settings are generalizable to individuals' routine time-use patterns and contexts of location, timing, duration, and sequence of health-related behaviors.

Population health interventions continue to be challenged with scaling effective implementation strategies to the contexts of heterogeneous populations and community settings [26]. Population health interventions include interventions to whole populations (e.g. regulatory restrictions on tobacco and alcohol sales) and interventions targeting subpopulations (e.g. age, ethnicity, health conditions) such as groups at greater risk of disease and harmful health outcomes (e.g. heart disease, alcohol dependence disorder) [28]. Adapting intervention components to fit different contexts is particularly important for transferring and scaling evidence-based interventions developed in high-income countries to low- and middle-income countries. However, decisions for adapting interventions to different contexts are complex, without clear guidelines for identifying potential mismatches (e.g. intervention goals, characteristics of the target population, implementation agency, and/or community) and factors influencing how implementation strategies can be altered to accommodate heterogeneous population characteristics, delivery system, and community context [28].

Part of this challenge is in the way population health interventions are commonly designed without behavior change theory [29], and information to assess contexts of individuals' unique spatiotemporal patterns, such as the heterogeneity of health behaviors between individuals living in the same environment with similar social determinants of health. Information about day-to-day activities of heterogeneous populations, such as individuals with complex health needs, is critical for tailoring interventions to meet individuals where they are at different stages of readiness to change, resources for adapting health behaviors, and diverse range of health needs [30]. Methods and technologies to identify individual spatiotemporal patterns of health behaviors in real-time would likely lead to better large-scale implementation of effective interventions that are tailored to the contexts of community settings and when and where health behaviors occur.

Information about activity space (i.e. totality of activities and interactions with people and places over time), use of time, and factors influencing decision-making is important for individuals and healthcare professionals. Individuals may not fully understand how to adjust their routine behaviors that have become automatic over time, and healthcare professionals may not be aware of the importance of using the context of activity space to adjust intervention techniques and encourage individuals with developing their own interventions based on when, where, and why their behaviors occur. For example, knowing where and how individuals spend the majority of their time day-to-day, such as at work or home, physically active or sedentary is important for contextualizing their social determinants of health and identifying the most opportune time and place to increase physical activity. Individuals working shift, part-time, and erratic hours could develop their own strategies such as setting reminders to move and stretch every hour, incorporating active transportation to and from work, or scheduling a walking meeting. By visualizing and characterizing key spatiotemporal contexts about an individual's day-to-day routine, insight can be gained about where and for how long activities occur and what opportunities exist for adapting day-to-day routines that can impact health outcomes.

A new approach is required to strengthen behavior change interventions by integrating contexts of time and activity space so that effective implementation strategies can be scaled across populations to influence how individuals make decisions about improving their health behaviors. Incorporating ideas from health geography and behavioral economics into the design of behavior change interventions provides an opportunity to collect and investigate individual-level health information to strengthen behavior change interventions for the prevention of chronic disease. This paper will discuss how theory from health geography could be applied to understand contexts influencing behaviors and how spatiotemporal information could be applied for the purpose of tailoring behavioral economic strategies to strengthen the design of behavior change interventions.

Health geography

Health geography contributes important insight for understanding multilevel factors influencing health behaviors and interconnections between place and health-related phenomena [27, 31]. Health geography demonstrates how health-related phenomena are inherently spatial such as geographic distributions of disease, patterns of health inequities across communities, and utilization and accessibility of health services across built environments [32, 33]. Ecological models are among the most well-known approaches for examining multilevel factors influencing health behaviors, including individual, social, and cultural environments in which health behaviors occur [34, 35]. By conceptualizing health within a sociospatial framework, valuable insights can be applied to public health challenges including reducing the prevalence of chronic diseases. We discuss how insights from spatial and temporal scale could improve our understanding of contexts influencing behaviors and why this information is important for strengthening behavior change interventions.

Spatiotemporal scale

The spatiotemporal dimensions of an individual's activity space are characterized by different environments, locations, and spaces an individual interacts with as a result of their activities [36]. Theory from time geography [37, 38] explains an individual's unique activity space, or their totality of activities and interactions with people and places over time [39], should be understood on a continuous and sequential continuum of day-to-day activities [40, 41]. For example, emphasizing one activity such as moderate-to-vigorous physical activity does not account for how individuals spend long continuous periods of time being active or inactive throughout their day [42, 43]. Furthermore, it is unclear how the design of behavior change interventions account for heterogeneity among individual health behaviors across different geographical, social, cultural, and political environments. For example, behavior change interventions most commonly use experimental designs (i.e. Randomized Controlled Trials) to deliver a standardized intervention by controlling for behaviors and measuring a targeted behavior change outcome [18]. Yet an individual's unique activity space is influenced by contexts of geographical, social, cultural, and political environments that largely determine day-to-day health behaviors [44, 45]. For example, patients with chronic kidney disease are typically challenged with maintaining stable routines due to the unpredictability of accessing health services and the ripple effect of having to adapt day-to-day routines around healthcare appointments [2]. Contextualizing social and spatial networks provides important insight for characterizing interactions and decision-making processes of activity space [46] so that behavior change interventions can be tailored across different geographical, social, cultural, and political environments.

Temporal contexts of health behaviors are more complex than multiple data points over time. There is deeper meaning to understanding contexts of health behaviors at different temporal scales [47] including length of residence, experiences and perceptions of space, place, and social relationships throughout the life course, and time of day. For example, length of residence is important for investigating long-term exposures to environmental conditions contributing to cancer [48], and social integration through connections to people and places that develop during longer-term residence (>13 years) in neighborhoods [49]. Health behaviors are also influenced by experiences and perceptions throughout the life course, such as gradual changes from transitions in school (i.e. primary to secondary, high school to post-secondary), or key life events (i.e. becoming a parent, retirement) [50]. The time-of-day and time-of-year activities occur provides important individual-level context [51] including opportunities and constraints for adapting day-to-day health behaviors according to patterns of time surplus and deficits. For example, individuals constrained by chronic time deficits, known as time poverty, commonly spend over 80 hours a week on employment and caregiving responsibilities and are more likely to experience barriers to physical activity, sleep deprivation, and high stress leading to negative mental health outcomes [52]. Understanding health behaviors using different temporal scales provides important insight for identifying past and present contexts influencing patterns in behaviors including when and how to intervene to support development of lifelong health-improving behaviors.

Methods to assess spatiotemporal contexts

Methods used to assess contexts of health behaviors include time-use techniques, ecological momentary assessment (EMA), geographically explicit ecological momentary assessment (GEMA), and geo-ethnography (see Table 1).

Time-use diaries are one example of quantitative techniques for documenting how individuals spend their time [60], and bring awareness to where and why individuals experience challenges with adapting their day-to-day activities. For example, time-use diaries have been used to assess when and where individuals adjusted their daily activities during different phases of COVID-19 public health restrictions in the UK [61]. EMA is a more widely used mixed-methods approach for gathering repeated real-time information on participants' behaviors, perceptions, and emotions, when they occur in natural environments [62, 63]. EMA involves an electronic device to notify participants at fixed or random times throughout the day to respond to survey questions and report their behaviors and environmental conditions during everyday activities [58]. For example, EMA has been used to understand the social and environmental contexts of children's leisure physical activity behaviors, indicating children reported the largest proportion of time physically active with family members and friends, when outdoors at a park or trail, and felt very safe [62]. Advancements to EMA methods include the use of location-tracking devices like global positioning systems (GPS) so the timing of EMA notifications are linked to participants' location where specific events occur [64–66]. For example, GEMA has been used to examine situational and locational factors associated with young adult substance use [67] such as smoking behaviors for economically disadvantaged young adults enrolled in a cessation program [68]. Findings indicate proximity to tobacco retail outlets within 1 mile of younger adult's home was associated with stronger urges to smoke [68]. Lastly, geo-ethnography is a mixed-methods approach combining qualitative ethnography and geographic information systems (GIS) to better understand contextual descriptions of what, when, why, and with whom activities occur [45]. Geo-ethnography involves in-depth interviews to gather contexts of participants' daily activities and lived experiences, with geographically explicit questions to derive locations and characteristics of the built environment that can be used to develop a visual map of participants' activity space [45, 69]. For example, geo-ethnography has been used to explore how food insecurity influences when, where, and how women living in urban and rural communities make decisions about shopping for food [69]. Different quantitative and mixed-method spatiotemporal approaches continue to advance our understanding of contexts influencing health-related behaviors, including the way individuals interact with and experience place [70].

The effectiveness of behavior change interventions is enhanced by incorporating knowledge about the spatiotemporal nature (or characteristics) of patient health behaviors. For example, measurement and visualization of patient activity spaces may help to identify opportunities for modifying day-to-day routines [2]. Understanding where and when patient health behavior occur is critical for providing direct feedback to individuals about why certain habits have formed either knowingly or not, while also equipping care providers and individuals with information to develop their own intervention strategies based on when and where to effectively disrupt their routine to encourage health-improving activities. A significant shift toward prevention requires investments in understanding the spatial and temporal contexts of health

Table 1 Methods to assess spatiotemporal contexts

Method	Description
Quantitative	
Time-use techniques	a. Time-use diaries use semi-structured fields to prompt participants with self-reporting details of their continuous activities and behaviors (i.e. time, activity, place, alone/with others) through a 24–48-hour period, often in 15-minute epochs [53]. b. Time-use surveys use a structured questionnaire to collect information about how participants allocate their time among different types of activities during the day, such as paid work, sleep, housework, physical activity, personal care, family tasks, and leisure activities [54].
Global Positioning Systems (GPS)	Satellite-based global navigation system provides precise location and time of any point on the Earth's surface [55].
Mixed method	
Geo-narrative	Explore temporal and spatial dimensions of daily activity patterns through quantitative 3D visualizations of space-time paths with contextual experiences linked to activities through time-use diaries. Space-time activity density surfaces can be used to understand the intensity of activity space derived from where, when, and for how long individuals spend time [56].
Geo-ethnography	Combine qualitative ethnography and geographic information systems (GIS) to gather in-depth descriptions of daily activity patterns. Geospatial data are derived from geographically explicit questions and used to develop visual maps of participants' activity space patterns [45].
Geo-questionnaire	Combine mapping software with open-ended and closed survey questions to collect public preferences, behavioral patterns, and spatially explicit knowledge. Using an interactive map, participants can respond to questions using free-hand sketches of points, lines, and/or polygons. Supplemental questions are triggered as participants use tools for object sketching and interact with the map [57].
EMA	Use of an electronic device to notify participants at fixed or random times to respond to open-ended and closed survey questions and report their behavior and environmental conditions during everyday activities [58].
GEMA	Combine location-tracking devices like GPS with EMA techniques so the timing of notifications is linked to participants' location where specific events occur and allow for time-stamped locations of collected EMA responses [59].

behaviors, so that individuals can develop their own strategies for self-management and modifying behaviors based on when and where their routine behaviors occur.

Behavioral economics

Discussion of spatiotemporal contexts of health behaviors raises an important question; when, where, and what intervention strategies would be most effective to disrupt day-to-day routines and encourage the development of health-promoting behaviors? The timing and location of behavior change intervention strategies could be just as important as the strategy employed for shifting decision-making processes. Research has not yet combined theory and methods from other disciplines, such as health geography with behavior change frameworks to tailor intervention strategies based on the contexts of when, where, what, and with who routine day-to-day behaviors occur. We discuss the potential for strengthening behavior change interventions by using spatiotemporal information to identify the most opportune time and place to tailor behavioral economic intervention strategies.

Behavioral economics, rooted in psychology and economics, explains that individuals commonly default to heuristics and cognitive biases, known as fast-thinking processes, that are automatic and emotionally charged and less commonly use slow, deliberate, and analytic thinking processes to make decisions [71, 72]. Behavioral economic principles also recognize everyday decisions about health behaviors are not solely driven by intrinsic automatic or reflective thought processes, as individuals are heavily influenced by contexts around them including environmental stimuli that nudge decision-making processes [73]. A framework of common behavioral economic principles is defined (see Table 2) using the MINDSPACE acronym: messenger, incentives, norms, defaults, salience, priming, affect, commitment, and ego [74].

Behavioral economic principles have been applied in behavior change interventions over the past 15 years and show promise for improving behavior change outcomes [75–77]. Behavioral economic principles improve behavior change outcomes within mobile health (mHealth) interventions for self-management of chronic conditions such as diabetes [78], increased physical activity within occupational [79, 80] and community-based settings [81], and reduced population consumption of foods high in sugar, sodium, and fat [82–84]. In the context of clinical interventions, incentives are the most widely adopted behavioral economic principle for increasing physical activity among patients [85, 86]. A meta-analysis of physical activity interventions shows modest financial incentives ($1.40 US/day) were associated with positive intervention effects and increased mean daily step counts during an intervention period of 12–23 weeks and post intervention after 17-week follow-up [87]. Despite the effectiveness of incentives, how incentives are delivered has been shown to influence the effectiveness of physical activity interventions [85]. When comparing differences between immediate versus delayed incentives, findings indicate immediate incentives are associated with greater physical activity outcomes from baseline in comparison to delayed incentives [88].

Evidence of effective behavioral economic strategies in different intervention settings is inconclusive due to heterogeneity of primary outcomes and method of delivering behavioral economic strategies [77, 85, 89]. For example, behavior change interventions using financial incentives to promote physical activity show variable outcomes when financial incentives are cash versus charitable donation [90]; payouts are delivered immediately versus delayed [88]; and when incentives are framed as losses compared with gains [91]. Further research is required to assess contexts influencing effective behavioral economic strategies including when, where, and how behavioral economic principles are delivered in behavior change interventions.

A criticism of behavioral economic intervention tools is that they lack coherence, focusing on automatic decision-making processes without adequately addressing reflective decision-making processes [92]. Behavioral economic tools also focus on applying external intervention functions (e.g. messenger, default, priming) to target behavior change [89], with minimal engagement from individuals to develop their own intervention strategies. Theory from health geography provides insight for addressing limitations of behavioral economic principles. For example, spatiotemporal information about day-to-day routines could be used to identify when and where individual behaviors are influenced by automatic versus reflective thought processes and how this information could support individuals with developing their own intervention strategies using behavioral economic principles.

Behavior change interventions have only recently, within the past 5 years, begun to integrate GPS technology with mHealth techniques so real-time locations of individual activity patterns can be used to tailor messages at the most opportunistic time and place for influencing behaviors [93]. For example, LowSalt4Life intervention [94] aims to reduce consumption of high sodium foods by collecting users' dietary diaries from foods consumed and purchased. Users are prompted to upload photos and provide geotags of where food is consumed and purchased (i.e. home, restaurant, grocery store) to predict the most opportunistic time to send just-in-time adaptive messages as users enter restaurants and grocery stores. LowSalt4Life messages are tailored to provide low sodium alternative menu options and recipes [94]. Just-in-time adaptive intervention techniques are one example of advancing mHealth and sensing technologies that have the potential to deliver the right type and amount of support, at the right time, by collecting real-time activity patterns and adapting to an individuals' unique contexts [95]. We provide recommendations of how behavior change interventions could be enhanced at scale by integrating theory and principles from health geography and behavioral economic principles (Table 3).

Space-time Continuum of Behavior Change Interventions

Improving behavior change interventions for the prevention of chronic disease requires a better understanding of health-related behaviors, specifically the way individuals interact with the environment and factors influencing decisions about day-to-day health behaviors. Behavior change frameworks like the Behavior Change Wheel (BCW) [92] and the Theoretical Domains Framework (TDF) [100] provide knowledge for understanding and determining influences on behavior and designing behavior change interventions. Three layers comprise the BCW (Fig. 1.1) including a center-hub (green) conceptualizing individual behaviors as functions of capability, opportunity and motivation (COM-B), a second layer of nine potential intervention functions (red), and

Table 2 MINDSPACE framework: definition of 9 constructs [74].

Construct	Definition
1. Messenger	We are heavily influenced by who communicates information. We are affected by the perceived *authority* of the messenger (whether formal or informal). Demographic and behavioral *similarities* between the expert and the recipient can improve the effectiveness of the intervention. We are also affected by the *feelings* we have for the messenger. We also use more rational and cognitive means to assess how convincing a messenger is.
2. Incentives	Our responses to incentives are shaped by predictable mental shortcuts such as *strongly* avoiding losses (we dislike losses more than we like gains), referencing points (the value of something depends on where we see it from), *overweighting* small probabilities (hence why lotteries may act as a powerful motivation), *mental* budgets (allocating money to discrete bundles), *present bias* (we prefer more immediate payoffs).
3. Norms	We are strongly influenced by what others do. Social and cultural norms are the behavioral expectations, or rules, within a society or group. Norms can be explicitly stated or implicit in observed behavior. People often take their understanding of social norms from the behavior of others. Relate the norm to your target audience as much as possible and consider social networks.
4. Defaults	We "go with the flow" of pre-set options. Many decisions we take every day have a default option, whether we recognize it or not. Defaults are the options that are pre-selected if an individual does not make an active choice. Defaults exert influence as individuals regularly accept whatever the default setting is, even if it has significant consequences.
5. Salience	Our attention is drawn to what is novel and seems relevant to us. Our behavior is greatly influenced by what our attention is drawn to. People are more likely to register stimuli that are *novel* (messages in flashing lights), *accessible* (items on sale next to checkouts), *simple* (a snappy slogan), and *relevant* (easier to grab attention at moments when people enter a new situation or life-stage such as moving house, going to university, pregnancy, etc.). We also look for a prominent *anchor* (such as unusual or extreme experiences, price, and advice) on which to base our decisions.
6. Priming	Our acts are often subconsciously influenced by cues in the environment. People's subsequent behavior may be altered if they are first exposed to certain sights, words, or sensations, which activate associated concepts in memory. In other words, people behave differently if they have been "primed" by certain cues beforehand.
7. Affect	Our emotional associations can powerfully shape our actions. Emotional responses to words, images, and events can be very rapid and automatic. Moods, rather than deliberate decisions, can therefore influence judgements. People in good moods make unrealistically optimistic judgements, whilst those in bad moods make unrealistically pessimistic judgements.
8. Commitments	We seek to be consistent with our public promises and reciprocate acts. We use commitments devices to achieve long-term goals. It has been shown that commitments usually become more effective as the costs for failure increase. One common method for increasing such costs is to make commitments public, since breaking the commitment will lead to significant reputational damage. Even the very act of writing a commitment is our strong instinct for reciprocity, which is linked to a desire for fairness.
9. Ego	We act in ways that make us feel better about ourselves. We tend to behave in a way that supports the impression of a positive and consistent self-image. We think the same way for groups that we identify with. We also like to think of ourselves as self-consistent. So, what happens when our behavior and our self-beliefs are in conflict? Interestingly, often it is our beliefs that get adjusted, rather than our behavior.

third layer of seven categories for types of policies to deliver intervention functions (white) [92]. The TDF, comprising 14 theoretical domains, offers practical guidance for assessing implementation and other behavioral problems and supporting intervention design [100]. These frameworks account for multilevel (i.e. individual, social, and environmental) determinants of behavior and intervention mechanisms to aid in understanding behaviors and implementing behavior change techniques. However, existing frameworks could be strengthened by integrating theory and principles from health geography and behavioral economics (Fig. 1.2) to contextualize how space and time are key factors influencing where and when intervention strategies could be tailored.

Space-time continuum

Incorporating ideas from health geography and behavioral economics into the design of the BCW (see Fig. 1) contributes new insight by identifying how spatiotemporal patterns (yellow wheel) and behavioral economic principles (blue wheel) are key influences on the contexts of behavior. Spatiotemporal contexts are comprised of patterns in behaviors across space, connections to place, time management, and patterns in behavior over time. A 24-hour clock around the outside of the spatiotemporal wheel emphasizes behaviors occur continuously with variability in the range of activities that occur throughout each day or more generally across time. For example, isolating one behavior like vigorous physical activity conveys very little about the totality of other activities occurring day-to-day including when, where, and for how long individuals engage in light, moderate, or sedentary activities. Understanding behaviors on a time continuum provides insight for understanding how individuals move throughout their day including sequential patterns in behaviors that form structured day-to-day routines, such as the time individuals wake up, the commute they take to work, how they spend continuous periods of time throughout the day, and types of leisure activities they engage in before going to bed.

Table 3 Recommendations to enhance behavior change interventions

Intervention	Description	Recommendations
Interventions integrating health geography theory		
"MyDayPlan" [96]	mHealth intervention targeting physical activity by encouraging users to set daily step count goals and specify when, where and how they plan on achieving their goals. MyDayPlan integrates a Fitbit activity tracker to monitor step count. Users receive a notification at 8 a.m. to set daily step count and time management goals and again at 8 p.m. to review step count activity and reflect on barriers and possible solutions for improving step count and time management the following day.	MyDayPlan notifications could be tailored using behavioral economic principles priming and commitments to encourage users with achieving daily step count goals. Contextual information of when, where, and how users plan on being physically active could be used to tailor time sensitive primes to encourage switching between tasks and increasing social commitments by encouraging users to schedule physical activity with family and friends.
"Drinkaware" [97]	mHealth intervention targeting alcohol-related harm by encouraging users to reduce risky alcohol consumption behaviors. Users are encouraged to track alcohol consumption, set goals to reduce alcohol consumption, gain feedback on how alcohol impacts health, and define locations of high risk for alcohol consumption. Drinkaware uses GPS data to send users supportive messages when they reach high-risk locations to break risky drinking behaviors.	Drinkaware notifications could be tailored using behavioral economic principles defaults, affect, and commitments. Notifications could be enhanced by supporting users with changing default alcoholic drink choices by providing nonalcoholic options before users enter establishments where alcohol is available. Automated notifications could be enhanced using affect to elicit emotional responses from tailored messages with images and descriptions about the harmful effects of alcohol consumption. Drinkaware could increase commitments by connecting users in the community with options for low-risk and dry social activities.
Interventions integrating behavioral economic principles		
"Carrot Rewards Program" [81, 98]	mHealth intervention targeting physical activity by incentivizing users with reward points to achieve their individualized daily step goals. Users are immediately rewarded with loyalty points (e.g. movies, grocery, gas, travel) when they refer friends, complete educational health quizzes, and achieve their daily step count goals.	Carrot Rewards incentives could be tailored using GPS data to collect information about when and where users are physically active and characteristics about their daily routines. Spatiotemporal information could enhance delivery of notifications for users to engage in physical activity by breaking up long periods of sedentary activity when users are at home or working.
"WalkMore" [99]	mHealth intervention targeting physical activity using just-in-time adaptive techniques to identify opportunistic times for priming users with messages that encourage walking. WalkMore uses smartphone and smart watch data to detect four opportunistic times for sending messages including, (i) users are on their smartphone for extended periods of time, (ii) users are sedentary for long periods of time, (iii) users are already walking, and (iv) after meals. Priming messages are tailored to users' individuals daily step goals.	WalkMore priming messages could be tailored using GPS data to identify opportunistic times associated with where users spend their time and characteristics of nearby environments (i.e. parks, trails, walking paths, recreational facilities) that support physical activity. Priming messages could also be tailored with context-specific recommendations for physical activity other than walking, such as strength training, stretching, and playing sports based on when users are at home or away from home.

Behaviors across space

Day-to-day behaviors cannot be isolated and occur continuously across space. Behaviors across space refers to the collection of locations in which activities are performed, known as activity space. An individual's unique activity space is influenced by where they live (e.g. proximity to services), constraints (e.g. time), and resources (e.g. transportation, financial) for participating in a range of activities within a potential path area [39]. Activity space has primarily been applied to explore spatial extents of travel within transportation planning [101], with fewer examples of activity space applied to contexts of health behaviors [102–104]. There lies an opportunity to explore the heterogeneity of health behaviors for individuals with expansive or spatially entrapped activity space. For example, an increase in virtual activity space from a range of online activities for employment, learning, and health care appointments [105] provides valuable information for tailoring intervention strategies based on where and how individuals spend long continuous periods of time, such as time spent at home or away from home.

Connections to place

Contexts of place are also critical factors influencing where, why, and with whom activities routinely occur. Context of place refers to the meaning individuals create from experiences, perceptions, and social relationships associated with activities occurring in physical locations or symbolic settings [106]. Places are generally provided meaning (i.e. emotive, emblematic) from associations individuals have with natural settings (e.g. parks, beaches), functional spaces (e.g. school, work), and broad characterizations of spaces where day-to-day activities occur (e.g. neighborhood, community settings) [106, 107]. For

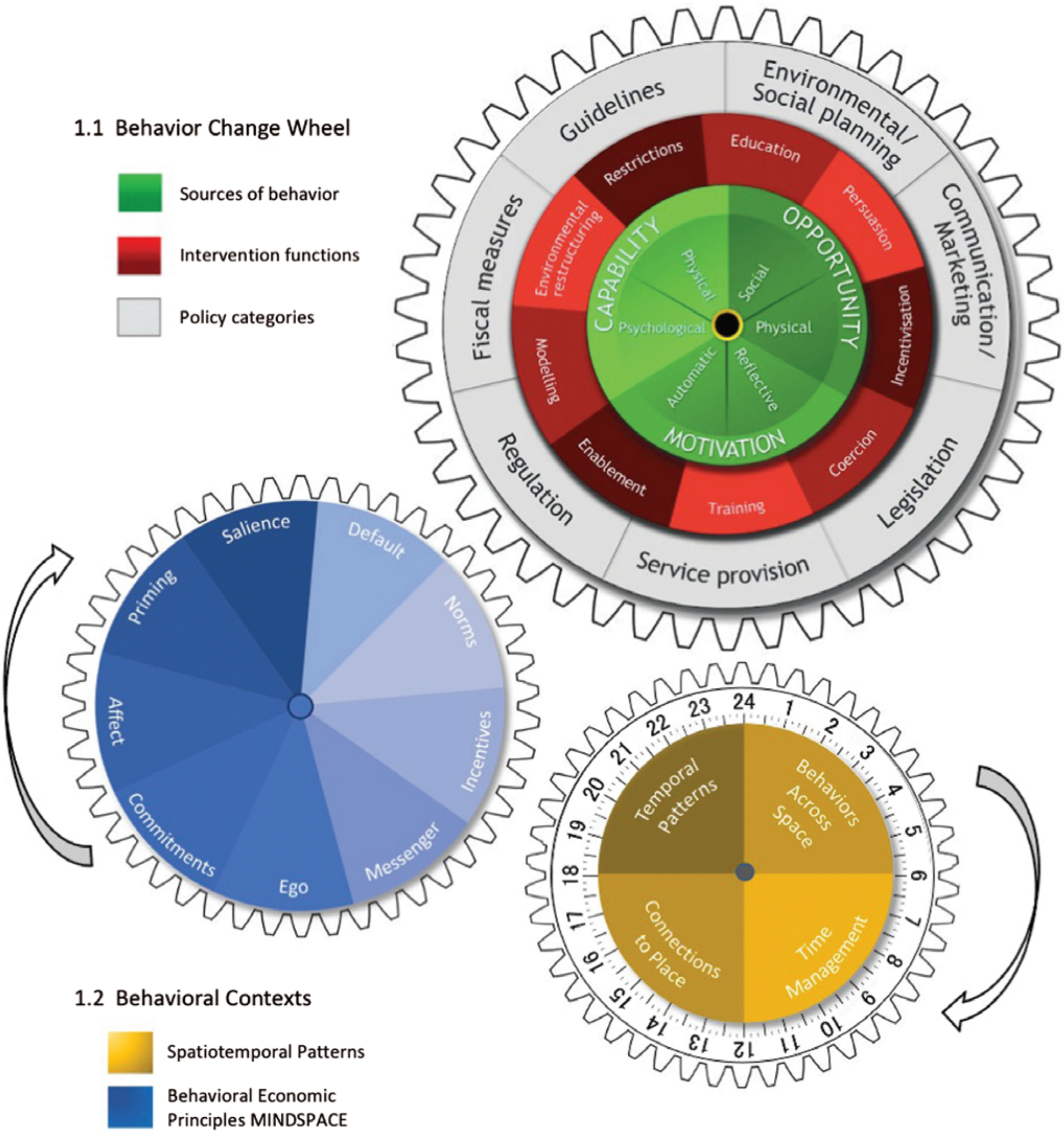


Figure 1 Space-time continuum of behavior change

example, adolescent perceptions of places and spaces promoting physical activity show built environments at home, and within neighborhoods are associated with increased physical activity [108]. Characteristics of places and spaces promoting physical activity show adolescents spend more time being physically active in the places between, as part of the journeys between neighborhood locations such as active commutes to and from school according to urbanicity [109]. Understanding contexts of place, such as positive versus negative experiences, perceptions, and social relationships could strengthen behavior change intervention strategies by identifying places and spaces that make behavior change easier and enjoyable.

Time management

Where (space and place) behaviors occur are influenced by contexts of time, including frequency, duration, and timing of activities. Although time is commonly referenced through discrete hours in a day, all hours are not equal [52]. The contexts of time, including individual resources (e.g. socio-economic), opportunities (e.g. flexible work schedule), and constraints (e.g. proximity to resources) are important for understanding how individuals organize and manage day-to-day routines. Structuring daily tasks and managing time for activities of daily living is critical for supporting behavior change and disease self-management strategies [1]. However individual-level contexts of time are rarely integrated to understand barriers and facilitators to managing time and strategies for supporting development of time-management skills to improve self-management [110, 111]. Contexts influencing time management are important for supporting individuals across diverse contexts, especially individuals with diverse backgrounds and social determinants of health that experience barriers from chronic time deficits [52, 112]. Individual-level information about the timing and duration of activities provides insight for tailoring interventions and for supporting individuals to develop their own time management strategies by identifying how to adapt day-to-day routines based on personal resources, opportunities, and constraints.

Temporal patterns

Patterns of behavior and contexts in which they occur change over time. Temporal patterns refer to the accumulation of day-to-day activities and experiences influencing health behaviors across an individual's life course. Temporal patterns include contexts spanning multiple time periods, such as patterns of past behaviors that influence present and future patterns of behavior [47]. Routine behaviors that develop over time, including behaviors contributing to obesity from childhood into adulthood [113], emphasize the need to intervene at multiple points in time throughout individuals' life course. Without information on individual level temporal patterns of health behaviors, it is challenging to understand the point in time interventions would be most effective. For example, an individual's residential address is commonly used for practical purpose of recording identification and contact information and recorded at present time in health administrative records. Yet length of residence and history of previous residence is important for understanding contexts of space and place influencing behaviors throughout the life course [50], changes in health behaviors such as physical activity associated with moving neighborhoods [114], and lifelong exposure to environmental conditions contributing to risk of disease [48].

Behavioral economic principles

Information about contexts influencing behaviors is critical for tailoring intervention strategies and identifying the most opportune time and place to adapt day-to-day activities. Behavioral economic principles (blue wheel) are commonly applied as intervention strategies within controlled clinic-based settings [85, 89] and legislative regulations [74]. However, it is not clear how behavioral economic principles are applied as tools for educating individuals about contexts influencing their behaviors, so they are active partners in developing their own intervention strategies. Individuals may benefit from learning about behavioral economic principles to understand how automatic and reflective thought processes influence day-to-day activities, strategies for resisting influence from environmental stimuli, and when and where decisions about engaging in health-improving activities could be easier and routine. Coupling spatiotemporal contexts with behavioral economic principles provides new perspectives for engaging individuals as partners for co-developing their own intervention strategies that can be adapted to contexts of their day-to-day activities and living conditions.

Integrating theory and principles from health geography and behavioral economics

To visualize how health geography and behavioral economics could be integrated within behavior change frameworks, such as the BCW, an adapted framework is presented (Fig. 2).

Spatiotemporal patterns (yellow layer) are integrated with individual sources of behavior (green layer) to conceptualize external contexts influencing an individual's intrinsic capability, opportunity, and motivation for behavior change. For example, physical opportunity within the COM-B model does not account for the complex relationships individuals have with their environment, how individuals interact with one another across built environments, and how complex health issues connect people, time, and place. Spatiotemporal patterns could improve how we understand behaviors and contexts influencing behaviors, so intervention functions (red layer) adequately target complex issues connected in space, place, and time.

Each of the behavioral economic principles (blue layer) included within the MINDSPACE framework relate to the BCW, as outlined by West and Michie [115] (see Supplementary Appendix A). Despite commonalities, intervention functions in the BCW are commonly tailored to intrinsic reflective decision-making processes [92, 116], whereas behavioral economic principles use generalizations about automatic behaviors, cognition or emotion to inform external intervention techniques [117]. Integrating behavioral economic principles with spatiotemporal patterns could enhance the delivery of intervention functions and policy categories by identifying the most opportune time and place individual behaviors could be influenced by intervention techniques targeting automatic versus reflective decision-making processes. Furthermore, integrating behavioral economic principles into intervention functions and policy categories could provide opportunities for individuals to be engaged with developing their own intervention strategies. Information about behavioral economic principles, such as priming and defaults could support individuals with creating their own environmental cues to restructure opportunities for making decisions that align with their behavior change goals.

The outer layer of the adapted BCW incorporates a 24-hour clock to signify temporal context of behavior change interventions, such as the timing and location of intervention techniques, effectiveness of interventions over time, and applicability of policy categories given fluctuating social, political, and economic contexts over time. For example, the timing in which population-wide masking policies were implemented was an important factor in limiting the spread of COVID-19. However, the applicability of population-wide masking policies has shifted in a relatively short time, from 2020 to 2023, based on different social, political, and economic contexts [118]. Sustaining behavior change interventions requires continual adjustments to adapt to changing contexts of the target population, social, cultural, community, financial, and environmental conditions in which they are applied. When evaluating the implementation and outcomes of intervention techniques, spatiotemporal contexts could provide important insights for tailoring behavioral economic strategies and identifying when and where intervention techniques need to be adjusted to maintain or improve effectiveness after repeated exposures. For example, behavioral change strategies that integrate behavioral economic principles may be successful at one moment in time, yet it is unclear whether the effectiveness of certain behavior change techniques decrease as they are repeated and recipients become accustomed to the same technique over time [119].

Strengthening behavior change interventions: Linking theory with technology

Strengthening behavior change interventions will require a multidisciplinary approach, such as linking theory with technology-based strategies to improve information about individual-level contexts of health behaviors, ideally in real-time and across different contexts. Technology-based methods allow us to bring together different types of data with a better understanding of individual behaviors and local contexts in which they occur. Technologies such as smartphone applications, wearable fitness devices, and medical sensors

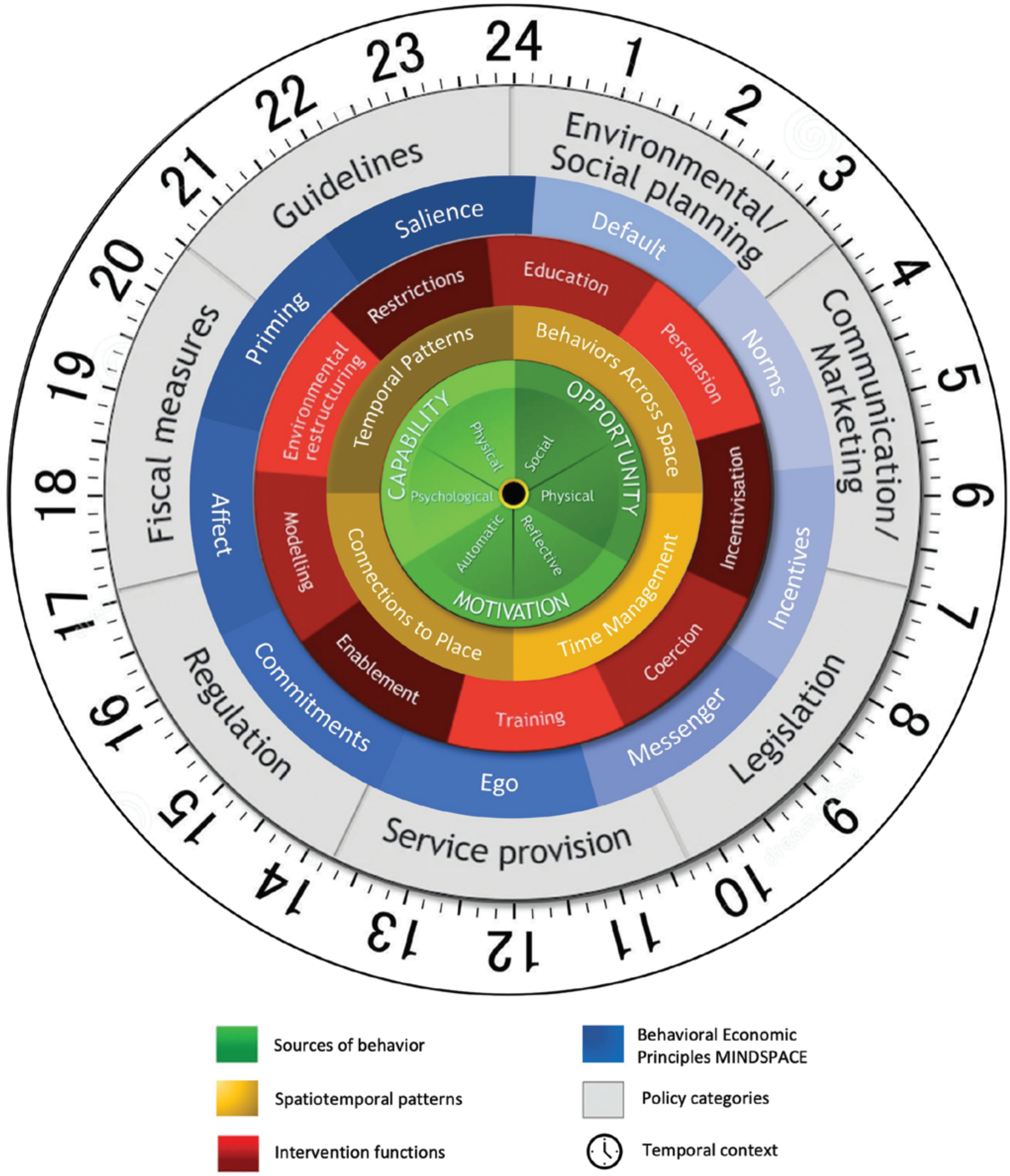


Figure 2 Integration of health geography and behavioral economic principles

are commonly part of intervention strategies and improve data for monitoring individual health and behavior change outcomes [117, 120]. Similarly, interventions designed using behavioral economic principles have increased over the past ten years, including interventions using changing default settings, peer comparison, and introducing incentives targeting healthcare professional and patient behaviors [77, 86, 121]. We suggest the potential for combining multidisciplinary approaches like behavioral science, health geography, psychology, and computer science to bring together different individual-level data to strengthen interventions tailored to contexts in which behaviors occur.

Machine learning techniques (e.g. artificial intelligence, learning algorithms) are one potential strategy for analyzing information from vast and complex data sets while providing individualized outcomes [122]. Innovative methods such as just-in-time adaptive interventions are one example of techniques for providing tailored support at opportune times when individuals need assistance with monitoring and reducing harmful substance use [123, 124]. Advancements to methods like machine learning techniques and just-in-time adaptive approaches show potential for improving behavior change interventions; however, a critical challenge continues to be integrating different types of individual-level data so interventions can be tailored and scaled to different settings.

Combining theory from health geography and behavioral economic principles with technology of machine learning could improve tailored intervention strategies and resources for disease self-management. For example, wearable digital sensor-based glucose monitors continuously report blood glucose levels and provide near real-time monitoring of spikes or drops in glucose for managing Type 1 and 2 diabetes [125]. Continuous glucose monitors show increased precision of detecting changes to glucose measures and are commonly linked to a smartphone application to notify individuals of changes to glucose measures [125, 126]. Yet the effectiveness of sensor-based continuous glucose monitors is challenged by limited patient engagement and understanding of strategies to improve stable glucose levels [127, 128].

Spatiotemporal methods such as GEMA, provide a way of collecting information about individual patterns in day-to-day activities and unique activity-space profiles of individuals including the timing, location, and contexts of behaviors. By combining spatiotemporal information with machine learning techniques, the timing and location of behavioral economic principles could be tailored to the most opportune time and place for delivering personalized intervention strategies. For example, knowing day-to-day routines of when and where individuals eat dinner is important for tailoring the timing of intervention strategies, such as 15-minutes of moderate physical activity after a meal can reduce glucose spikes by 0.44 mmol/l [129]. Machine learning techniques also have the capability of analyzing vast amounts of individual-level data into interpretable patterns of health behavior so that individuals could be engaged as partners in reviewing information about when, where, and why glucose spikes occurred and co-developing their own intervention strategies for managing glucose levels.

Conclusion

In this paper we discuss how theory and principles from health geography and behavioral economics provide insight for tailoring behavior change interventions. The prevention of chronic diseases requires a multidimensional understanding of individual behaviors within the contexts in which they occur so that behavior change interventions can be tailored, implemented in different settings, and scaled to different populations. We suggest how theory and principles from health geography and behavioral economics provide insight for improving behavior change interventions. Linking theory with technology provides additional opportunities for using different types of data to understand behavioral contexts with technology tools to enhance tailored interventions that support individuals to develop their own intervention strategies.

Supplementary Data

Supplementary data is available at *Translational Behavioral Medicine* online.

Conflict of Interest Statement

All authors declare they have no conflicts of interest.

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Data Availability

De-identified data were not used in this study.

Analytic Code Availability

There is not analytic code associated with this study.

Materials Availability

Materials used to conduct the study are not publicly available.

Ethical Approval

This article does not contain any studies with human participants performed by any of the authors.

Informed Consent

This study does not involve human participants and informed consent was therefore not required.

Welfare of Animals

This article does not contain any studies with animals performed by any of the authors.

Transparency Statements

Study registration: This study was not formally registered. Analytic plan preregistration: The analytic plan was not formally preregistered.

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